

# **Asset Management Tools for Municipal Infrastructure Considering Interdependency and Vulnerability**

Ahmed Atef Youssef

A Thesis  
In the Department of  
Building, Civil, and Environmental Engineering

Presented in Partial Fulfillment of the Requirements  
For the Degree of  
Doctor of Philosophy (Building Engineering) at  
Concordia University  
Montreal, Quebec, Canada

April 2015

© Ahmed Atef Youssef, 2015

**CONCORDIA UNIVERSITY  
SCHOOL OF GRADUATE STUDIES**

This is to certify that the thesis prepared

By: Ahmed Atef Youssef

Entitled: Asset Management Tools for Municipal Infrastructure Considering Interdependency and Vulnerability

\_\_\_\_\_

\_\_\_\_\_

and submitted in partial fulfillment of the requirements for the degree of

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

<u>Dr.Georgios Vatistas</u>	Chair
<u>Dr.Jeffrey Hudson Rankin</u>	External Examiner
<u>Dr. Amin Hammad</u>	External to Program
<u>Dr.Ashutosh Bagchi</u>	Examiner
<u>Dr.Tarek Zayed</u>	Examiner
<u>Dr.Osama Moselhi</u>	Thesis Supervisor

Approved by

\_\_\_\_\_  
Chair of Department or Graduate Program Director

\_\_\_\_\_

\_\_\_\_\_  
Dean of Faculty

# **ABSTRACT**

## **Asset Management Tools for Municipal Infrastructure Considering Interdependency and Vulnerability**

**Ahmed Atef Youssef, Ph.D.**

**Concordia University, 2015**

Current asset management practices of municipal infrastructure focus on modeling water, sewer and road networks into isolated layers and hence overlook the spatial and functional interdependencies among these assets. For instance, the performance of an asset can be impacted spatially and/or functionally by its neighboring assets. Vulnerability assessment, in this study, measures the asset's degree of susceptibility for structural and/or functional failures triggered by failure of these functions in neighboring assets. The objective of this research is to develop a computational framework for optimizing intervention policies for likely vulnerable civil infrastructure networks considering spatial and functional interdependencies. The developed framework integrates three models; 1) interdependency assessment model, 2) vulnerability assessment model and 3) system dynamics model.

The interdependency assessment model captures spatially and functionally interdependent assets utilizing two developed modules: spatial interdependency module and functional interdependency module. The spatial module utilizes ArcGIS geoprocessing tools in determining geographically interdependent assets. It encapsulates interdependent assets in a set of new layers and a newly developed database containing characteristics of such interdependencies. On the other hand, the functional module employs graph theory principles in determining an asset's degree of connectivity with its neighboring assets. The functional module will aid in recognizing the likely

influence of an asset failure on its neighboring assets' performance using betweenness centrality. The output of the assessment model is in the form of bundles of spatially and functionally interdependent assets.

For vulnerability assessment, three computational models are developed and experimented with to rate vulnerability of civil infrastructure systems considering their spatial and functional interdependencies with neighboring assets. These models are; 1) multi-attribute utility theory (MAUT), 2) artificial neural network (ANN) and 3) fuzzy c-mean clustering (FCM). Operation and maintenance reports obtained from two Canadian municipalities (the Cities of London and Hamilton, Ontario) were used to select factors influencing the vulnerability of water, sewer and road assets. For the MAUT model and based on the identified factors from operation and maintenance reports, surveys were sent to 65 experts and their feedback was elicited to construct utility functions to rate the degree of vulnerability of interdependent assets. The response rate of the survey was 75%. On the other hand, the ANN model utilizes self-organized mapping algorithm (SOM) to rate vulnerability of these assets based on recognized patterns in each dataset. The ANN model is a data driven model requiring sufficient amount of observed patterns and extensive effort in modeling with less involvement from experts. On the other hand, the FCM model is capable of accounting for ambiguity and imprecision associated with experts' input in rating vulnerability of interdependent assets.

Subsequently, the system dynamics (SD) model is developed to help identify possible least cost intervention policies for interdependent infrastructure assets that meet customers' expectations and decrease assets' vulnerability. The developed SD model consists of 23 variables and 8 causal feedback loops. These causal loops are developed based on the reviewed literature and four unstructured interviews with three experts in the domain of municipal asset management; one from

the City of London and two from the City of Hamilton. The SD is augmented with two optimization algorithms to find optimal intervention policies at bundle and network levels; 1) dynamic programming algorithm, 2) single objective genetic algorithm.

Two case studies were analyzed and presented to demonstrate the application of the proposed framework and its expected contributions using data obtained from the Cities of London and Hamilton, Ontario. The interdependency model constructed 10,500 bundles for the City of London and 12,350 bundles for the City of Hamilton. For the vulnerability model, the developed FCM model showed better performance than ANN in mimicking experts' judgement. The mean square error (MSE) for the FCM model was 42% less than that of the ANN model. Also, there was a linear correlation between the number of breaks for water assets and their vulnerability ratings ( $R^2=0.79$ ). When the SD model was supplemented by the modified genetic algorithm, the computational time for finding near optimal solutions at network level was decreased by 50% for the City of London and by 47.2 % for the City of Hamilton when compared to traditional genetic algorithm.

The results of the developed vulnerability and SD models were shared with the experts. The developed vulnerability models will be useful for staff to justify increases to intervention budget to each City Council. In spite of the relatively complicated nature of ANN and FCM models, the experts were relatively comfortable using these models. However, the experts commented that this might not be the case with other municipalities that are still starting their asset management programs. For the SD model, the experts agreed that the model is beneficial for identifying possible least cost intervention policies at bundle and network level. They however pointed out that the SD model can be enhanced by accounting for factors related to social and economic characteristics of

their customers. The modified genetic algorithm can be enhanced more by the deployment of parallel computing techniques to decrease its computational time.

## **ACKNOWLEDGMENT**

All praise and thanks are due to Allah for giving me the patience and perseverance to successfully accomplish my Ph.D. study. This thesis is dedicated to my family for their endless support and encouragement throughout my life. Their unconditional love has been source of inspiration. I could never achieve this work without their endless encouragement and help.

I am greatly thankful to my supervisor Dr. Osama Moselhi for his invaluable guidance and patience with me throughout my studies. His valuable advice and commitment exceeded the call of duty and extended far beyond technical bounds. It was a great honor to work under his supervision.

I would like to acknowledge the support of Dr. Khaled Shehata by sharing City of London infrastructure network data and providing me with his feedback throughout the course of this research. Finally, I would like to thank all my colleagues in the Construction Automation Laboratory. And special thanks to Ali Montser, Magdy Omar, Ibrahim Bakry and Walaa Aldin for their encouragement and assistance. Your friendship is irreplaceable. I feel so lucky to have you in my life.

I wanted to express my sincere gratitude to my wife, Shaimaa, for all of her love, help and encouragement over the last four years. I never would have made it without you, Omar and Maryam.

# Table of Contents

List of Figures .....	xiii
List of Tables .....	xvii
List of Notations .....	xix
Chapter 1 : INTRODUCTION.....	1
1.1    General .....	1
1.2    Interdependency and Vulnerability Assessment .....	2
1.3    Problem Statement .....	4
1.4    Objectives and Motivation .....	5
1.5    Research Framework Overview .....	7
1.6    Thesis Organization.....	11
Chapter 2 : LITERATURE REVIEW.....	13
2.1    Introduction .....	13
2.2    Infrastructure Interdependency .....	15
2.2.1    Interdependency Classifications .....	15
2.2.2    Interdependency Models.....	17
2.2.3    Limitations of Interdependency Models .....	27
2.3    Vulnerability Assessment.....	28
2.3.1    Vulnerability Classification .....	29
2.3.2    Vulnerability Assessment Models .....	30



2.3.3	Limitations of Vulnerability Models .....	39
2.4	Intervention Actions .....	40
2.4.1	Water and Sewer Networks .....	40
2.4.2	Road Networks.....	45
2.5	Research Methods .....	46
2.5.1	Fuzzy Set Theory .....	46
2.5.2	Artificial Neural Networks .....	48
2.5.3	Optimization Models .....	50
2.6	Summary and Limitations in Current Research .....	52
Chapter 3 : DATA COLLECTION.....		54
3.1	Introduction .....	54
3.2	Remarks on Data Collection Process .....	55
3.3	City of London .....	55
3.4	City of Hamilton.....	63
3.5	Common Observations on the Collected Data .....	67
3.6	Summary and Conclusion .....	69
Chapter 4 : DEVELOPED RESEARCH FRAMEWORK .....		70
4.1	Introduction .....	70
4.2	Interdependency Assessment Model.....	72
4.2.1	Spatial Module .....	73

4.2.2	Functional Interdependency model.....	77
4.3	Vulnerability Models.....	82
4.3.1	MAUT.....	83
4.3.2	ANN.....	87
4.3.3	FCM.....	88
4.4	System Dynamics Model .....	92
4.4.1	System Dynamics.....	92
4.4.2	Casual Loop Diagrams.....	93
4.4.3	Stock and Flow Diagrams.....	93
4.4.4	Causal Loops.....	94
4.4.5	Stock and Flow .....	107
4.4.6	Dynamic Programming Algorithm .....	109
4.4.7	Single Objective Optimization Algorithm .....	113
4.5	Summary and Conclusion .....	117
Chapter 5 : COMPUTER IMPLEMENTATION .....		119
5.1	Introduction .....	119
5.2	Interdependency Assessment Model.....	119
5.2.1	Spatial Module.....	120
5.2.2	Functional Module.....	127
5.3	Vulnerability Model .....	130

5.4	System Dynamics Model .....	135
5.5	Summary and Conclusion .....	143
Chapter 6 : CASE STUDIES .....		144
6.1	Introduction .....	144
6.2	City of Hamilton.....	144
6.2.1	Interdependency Assessment Model.....	145
6.2.2	Vulnerability Model.....	148
6.2.3	System Dynamics Model .....	150
6.3	City of London .....	153
6.3.1	Interdependency Assessment.....	155
6.3.2	Vulnerability Model.....	157
6.3.3	System Dynamics Model .....	159
6.4	Discussion of the Research Findings .....	162
6.5	Summary and Conclusion .....	164
Chapter 7 : CONCLUSIONS AND FUTURE WORKS .....		166
7.1	Summary and Conclusions.....	166
7.2	Research Contribution.....	168
7.3	Limitations .....	170
7.4	Future Work .....	171
References.....		173

Appendix A : Fuzzy Set Theory .....	181
Appendix B : MAUT Survey .....	196
Appendix C : Sample of the SD Output.....	219
Appendix D : Coding Samples .....	221

## List of Figures

Figure 1-1 Research framework overview.....	8
Figure 2-1 Chapter 2 overview .....	14
Figure 2-2 Network with adjacency matrix (adapted from Crucittia et al., 2003).....	19
Figure 2-3 I/O model for two sub-systems (Haimes & Jiang, 2001).....	22
Figure 2-4 General framework for Infrastructure Interdependency using SD (Stapelberg, 2011).....	25
Figure 2-5 SD model using feeding loops for water industry (Stapelberg, 2011).....	26
Figure 2-6 Vulnerability assessment and risk assessment process (Baker, 2003).....	31
Figure 2-7 Framework for vulnerability and risk assessment (Karmakar, et al., 2010) .....	33
Figure 2-8 Vulnerability assessment model (Ouyang et al., 2009).....	37
Figure 2-9 SD model for vulnerability assessment (Eun et al., 2010).....	38
Figure 2-10 Trenchless technologies classifications.....	43
Figure 2-11 Schematic ANN (Hegazy and Ayed, 1998) .....	49
Figure 3-1 Chapter 3 overview .....	54
Figure 3-2 Water network, London, Ontario .....	56
Figure 3-3 Sewer network, London, Ontario .....	57
Figure 3-4 Road network, London, Ontario.....	58
Figure 3-5 Condition ratings for water, sewer and road assets (SOI, 2013).....	59
Figure 3-6 Failure causes for water mains.....	61
Figure 3-7 Water database configuration, London .....	62
Figure 3-8 Road database configuration, London.....	63
Figure 3-9 Water and road network, City of Hamilton, Ontario .....	65
Figure 3-10 Water database configuration, Hamilton.....	66

Figure 4-1 Chapter 4 overview .....	72
Figure 4-2 Spatial interdependency model .....	75
Figure 4-3 The developed entity relationship diagram for the spatial module (water and road)..	76
Figure 4-4 Normalized and non-normalized degree of a vertex .....	79
Figure 4-5 The developed functional module algorithm .....	81
Figure 4-6 Vulnerability model overview.....	84
Figure 4-7 Weights of spatial factors (water and sewer assets).....	85
Figure 4-8 Weights of functional factors (water and sewer assets) .....	85
Figure 4-9 Weights of spatial factors (road assets).....	86
Figure 4-10 Weights of functional factors (road assets).....	86
Figure 4-11 The developed ANN algorithm .....	89
Figure 4-12 The developed FCM algorithm .....	91
Figure 4-13 Casual Loop of the developed SD model.....	96
Figure 4-14 R1 algorithm.....	98
Figure 4-15 Deterioration curve for the road asset .....	99
Figure 4-16 R2 algorithm.....	101
Figure 4-17 Decision maker's satisfaction from road condition .....	101
Figure 4-18 Effect of intervention action on road's condition .....	102
Figure 4-19 Effect of the intervention action on the decision maker's satisfaction from to road's condition .....	103
Figure 4-20 Decision maker's satisfaction from vulnerability of road assets .....	104
Figure 4-21 R3 algorithm.....	105
Figure 4-22 R4 algorithm.....	106

Figure 4-23 Stock flow with causal feedback loops .....	108
Figure 4-24 The developed dynamic programming algorithm .....	111
Figure 4-25 Sample of the dynamic programming network .....	112
Figure 4-26 Chromosome structure .....	114
Figure 4-27 The developed SOGA algorithm.....	115
Figure 5-1 Chapter 5 overview .....	119
Figure 5-2 Interactions between the end user and the two implemented modules .....	120
Figure 5-3 Spatial module and ArcGIS toolboxes.....	122
Figure 5-4 Spatial module user interface .....	123
Figure 5-5 Selecting the road network.....	124
Figure 5-6 Spatial module output .....	125
Figure 5-7 Implemented entity diagram for interdependent water, sewer and road assets.....	126
Figure 5-8 Converting ArcGIS map from mxd format to GML format .....	128
Figure 5-9 Functional module output .....	129
Figure 5-10 Interaction between the end user and vulnerability models .....	131
Figure 5-11 MAUT model for vulnerability assessment .....	132
Figure 5-12 Assigning weights for the utility functions in MAUT .....	133
Figure 5-13 MAUT output.....	134
Figure 5-14 Interaction between the end user and the developed system dynamic model.....	136
Figure 5-15 GUI for road asset inputs .....	137
Figure 5-16 The SD and dynamic programming output.....	138
Figure 5-17 GUI for the inputs of the two proposed supplemented algorithms .....	142
Figure 6-1 Chapter overview .....	144

Figure 6-2 A sample from the road network with asset's ID.....	146
Figure 6-3 RBC for water and road networks, Hamilton.....	147
Figure 6-4 Vulnerability rating for City of Hamilton using the MAUT model.....	148
Figure 6-5 Vulnerability assessment using the FCM model.....	149
Figure 6-6 Water asset deterioration curve.....	150
Figure 6-7 Comparision between traditional GA and modified GA.....	152
Figure 6-8 The best solution from the modified GA .....	154
Figure 6-9 RBC histogram for water, sewer and road assets, London .....	156
Figure 6-10 Vulnerability assessment for the water network using FCM .....	158
Figure 6-11 Vulnerability rating for water asset based on its condition.....	159
Figure 6-12 Comparison between traditional GA and modified GA.....	160
Figure 6-13 The best solution from the modified GA .....	161
Figure A-1 Fuzzy expert system steps .....	182
Figure A-2 Crisp set in classical logic (Yuan, 1995).....	182
Figure A-3 Fuzzy membership function for very tall people (Yuan, 1995) .....	183
Figure A-4 Fuzzy membership function for medium, tall and very tall people (Yuan, 1995) ...	184
Figure A-5 Defuzzification process .....	188
Figure A-6 Defuzzification of risk.....	189
Figure A-7 Pipe condition membership function.....	192
Figure A-8 Buried depth membership function .....	192
Figure A-9 Vulnerability rating membership function .....	192



## List of Tables

Table 3-1 Quantitative data attributes for water network, City of London .....	59
Table 3-2 Qualitative data attributes for water network, City of London .....	60
Table 3-3 Quantitative data attributes for sewer dataset, City of London .....	60
Table 3-4 Qualitative data attributes for road dataset, City of London .....	60
Table 3-5 Quantitative data attributes for water datasets, City of Hamilton .....	64
Table 3-6 Qualitative data attributes for water datasets, City of Hamilton .....	64
Table 4-1 Sources and purposes of R1 variables .....	97
Table 4-2 Sources and purposes for R2 variables.....	100
Table 4-3 Sources and purposes of R3 and R4 variables.....	104
Table 5-1 Summary of SD model variables .....	139
Table 5-2 Dynamic programming algorithm inputs .....	140
Table 5-3 SD and dynamic programming algorithm outputs .....	140
Table 5-4 GA inputs.....	141
Table 5-5 SD and GA outputs.....	141
Table 6-1 RBC for a sample from the road network, Hamilton .....	147
Table 6-2 Comparison between the three computational techniques for the City of Hamilton .	149
Table 6-3 Top ten scenarios for bundle number 1 .....	151
Table 6-4 Sample for the best solutions obtained at the network level from the modified GA algorithm .....	153
Table 6-5 Comparison between the three models for City of London .....	157
Table 6-6 Sample for the best solutions obtained at the network level from the modified GA algorithm .....	160

Table 6-7 Comparison between the three models .....	163
Table A-1 Pipe condition range .....	190
Table A-2 Buried depth range.....	191
Table A-3 Vulnerability rating range.....	191
Table A-4 Rule base matrix .....	193

## List of Notations

$a_{ij}$ : The Leontief technical coefficient

A: Adjacency matrix

ABM: Agent based modeling

AHP: Analytical hierarchy process

ANN: Artificial neural networks

$B_{\text{allocated}}$ : Available budget

$B_{\text{assigned}}$ : Assigned budget

bet(k): Betweenness centrality of vertex k

$C_i$ : The portion of industry  $i$ 's final production for end user consumption

C: The loss of a system due to external hazard

CAS: Complex adaptive systems

CL: Causal loop

CLD; Causal loops diagram

CPI: Condition performance index

Cst: Decision maker's satisfaction for current condition

CVAT : Community vulnerability assessment tool

D(t): Target input data vector

Deg( $V_i$ ): Degree of a vertex

DES: Discrete event simulation

DP: Dynamic programming

$E_{in}$ : Number of entering edges

$E_{out}$ : Number of exiting edges

FCM: Fuzzy c-mean

G: Graph

GA: Genetic algorithm

$g_{ij}(k)$ : Number of shortest paths between  $ij$  with vertex  $k$

GML: Geography markup language

Icost: Intervention cost

INL: Idaho National Laboratory

$L_{i,j}$ : Shortest distance between any two nodes

LCC: Lifecycle Cost

$L_{LOS}$ : The trigger LOS

LOS: Level of service

LOSst: Decision maker's satisfaction for current LOS

Lu: The trigger asset condition

$L_{VL}$ : The trigger vulnerability

$m_A(x)$ : Membership function

MAUT: Multi attribute utility theory

$n$ : Current time step

$N$ : Number of nodes in the network

NC is Neighborhood Centrality

$Neig(k)$ : Neighbourhood vertex centrality

$Norm\text{-}bet(k)$ : Normalized vertex betweenness centrality

$Norm\text{-}C(i)$ : Normalized centrality

$Norm\text{-}deg(V_i)$ : Normalized vertex degree

O&M: Operation and maintenance reports

OGC: Open geospatial consortium

RBC: Relative Betweenness Centrality

$S$ : Current iteration

SD: Systems dynamics

SF: Stocks and flow

SOGA: Single objective genetic algorithm

SOI: State of infrastructure report

SOM: Self organized maps

t: Simulation time

T: The deterioration matrix

$T_{LOS}$ : The target LOS

$Ts(w,s,r)$  : Decision maker's total satisfaction for water, sewer and road assets.

Tst: The total satisfaction

$T_u$  : The target asset condition

$T_{VL}$ : The target vulnerability

U: The current asset's condition

$U_{ij}$ : Utility score for the  $j^{th}$  attribute associated with the  $i^{th}$  asset

$u_v$ : the index of the best matching unit (BMU) in the map

VBA: Visual basic application

$V_i(T_s)$  : Decision maker's total satisfaction due to certain combination of intervention actions at time step n for water, sewer and road assets

$VLst$ : Decision maker's satisfaction for current vulnerability

$W_c$ : Weight for satisfaction from asset's condition

$W_j$  : Weight assigned to attribute j

$W_{LOS}$ : Weight for satisfaction from LOS

$W_v$ : The current weight vector of node v

$W_{VL}$ : Weight for satisfaction from current vulnerability

$X$ : Member of a collection of objects

$X_i$  : The total production output from the industry

$Z$ : The objective Function

$\Theta(u, v, s)$  : A restraint due to distance from BMU

$\Lambda$ : The iteration limit

# **Chapter 1 : INTRODUCTION**

## **1.1 General**

Infrastructure asset management aims to maintain the public capital intensive assets in a condition that meets community preferences and decreases likelihood for catastrophic failures. The 2013 infrastructure report card of (American Society of Civil Engineering) ASCE rated the condition of water, sewer and road infrastructure networks in the United States as D; indicating that these infrastructure networks are in poor condition and mostly below standard, with many assets approaching the end of their service life. The report also stressed that a large number of these assets exhibits significant deterioration with enormous concern over their future condition and capacity. Catastrophic failures of asset management are mainly due to deterioration in physical resilience of assets with time. Therefore, the performance and operation modeling of these systems have been developed to support planning, maintenance, and retrofit decision making from multiple view points, including infrastructure owners or investors, private and public users, and government entities.

Generally, the models described in the literature focus on isolated analysis of infrastructure assets for a specific domain (i.e. water, sewer, roadways...etc.); ignoring spatial and functional interdependencies. For instance, this approach seems to be inappropriate as the function of road asset may be affected by failure of a nearby water asset. This depicts spatial vulnerability. Also, the propagations of such failure on other parts of the water network can be disastrous depending on the number of customers that will be affected and the category of these customers. This depicts functional



vulnerability. In July 2014, a water pipeline break flooded the Sunset Boulevard of California and parts of UCLA campus, discharging 8 to 10 million gallons of water; resulting in catastrophic social and economic consequences (Yan and Almasry, 2014). This water pipeline breakage generated a power failure, disruption to functionalities of nearby water, sewer and road assets and resulted in diminishing power and water recourses needed for firefighting (Yan and Almasry, 2014). In California, an electric power disruptions in early 2001 affected oil and natural gas production, refinery operations, pipeline transport of gasoline and jet fuel within California and to its neighboring states, and the movement of water from northern to central and southern regions of the state for crop irrigation (Rinaldi et al., 2001). The cascading effects to this catastrophe has idled key industries which led to billions of dollars of lost productivity, and stressed the entire Western power grid, causing far-reaching security and reliability concerns. Additionally, the ice storm in January 1998 in Quebec caused a huge power failure, disruption of water supply and sanitation systems, traffic chaos and resulted in diminishing power and water recourses needed for firefighting (Moselhi et al., 2005). Such catastrophic events and others necessitated the study of infrastructure interdependency, vulnerability assessment and mitigation action modeling of critical infrastructure systems (Crucittia et al., 2003; Gesara and Osorio, 2010; Roshani and Filion, 2014; Wu et al., 2014; Laucelli and Giustolisi, 2014).

## **1.2 Interdependency and Vulnerability Assessment**

Infrastructure systems interdependency is a rapidly growing area of study with contributions from multiple researchers in various engineering, mathematical and social science disciplines (Rinaldi et al., 2001). It primarily focuses on aiding decision makers

to achieve national security, economic prosperity, and quality of life (Gesara et al., 2010). Such economic and social prosperity is attained while heavily depending on the continuous and reliable operation of critical interdependent infrastructure systems. The study of interdependent infrastructure systems is challenging due to heterogeneous characteristics of infrastructure systems, insufficient data and the need to account for their spatial and functional aspects and its effect on supply-demand operation (Gesara et al., 2010). Researchers have attempted to model various types of interdependencies; (i.e. spatial, functional, social, economic....etc.) as will be discussed in Chapter 2. In this research, only spatial and functional interdependencies are considered. In this study, spatial interdependency addresses whether an infrastructure's structural integrity or performance is threatened by being located in the same geospatial area of neighboring assets (Rinaldi et al., 2001, Tushith and Moselhi, 2010). Also, Functional interdependency assesses to which degree the performance of infrastructure is impacted by the structural integrity or performance of a neighboring asset (Rinaldi et al., 2001, Dudenhoefter et al., 2006).

On the other hand, vulnerability, in this research, is defined as the degree of susceptibility to structural or functional failures as a result of being interdependent with neighboring assets (Atef and Moselhi, 2014). Hence, there are two types of vulnerabilities: 1) spatial vulnerability and 2) functional vulnerability. Vulnerability assessment is the process of identifying systems' weaknesses due to specific events and assessing the extent of such weaknesses on systems' performance or existence (Baker, 2003).

As will be shown in the literature review chapter, modeling of spatial and functional interdependencies and their impact on vulnerability of civil infrastructure networks is not considered in current asset management practices (Orabi and El-Rayes, 2012; Roshani and Filion, 2014; Mandapaka et al., 2012). Previous decision support systems (DSS) were designed and implemented ignoring the underlying spatial and functional interdependencies that exist between water, sewer and road networks (Moselhi et al, 2005). Also, studies on vulnerability and interdependency modeling focused primarily on disaster management applications ( Ezell, 2005; Karmakar et al., 2010; Eun et al, 2010; Ouyang et al., 2009; Osorio et al., 2007).

### **1.3 Problem Statement**

The main limitations with respect to this research in current state of the art of asset management of municipal infrastructure can be stated as:

- 1- Previous DSS for rehabilitation and maintenance policies were primarily implemented ignoring underlying spatial and functional interdependencies that exist between water, sewer and road networks.
- 2- For interdependency models, current models were oriented towards assessing functional and/or economic interdependencies between various interacted networks for disaster management (Santos & Haines, 2004; Osorio et al., 2010; Karmakar et al., 2010; Roshani and Filion, 2014). In asset management, decision makers maintain public capital intensive assets to meet customers' expectations not only to avoid catastrophic failures.
- 3- For vulnerability models, current state of the art focuses on studying independently factors affecting vulnerability due to spatial interdependency and

function interdependency (Roshani and Fillion, 2014; Mandapaka et al., 2012; Wei et al, 2009).

4- For interdependency and vulnerability models:

- i. Previous studies fail to objectively allocate the diminished resources for intervention policies on network levels (Ezell, 2005; Ouyang et al., 2009; Osorio et al., 2010).
- ii. Previous studies did not consider operation and maintenance reports of civil infrastructure networks in understanding causes for increasing or decreasing vulnerability of interdependent assets (Ezell, 2005; Karmakar et al., 2010; Flax et al., 2003; Wu et al., 2014; Laucelli and Giustolisi, 2014).
- iii. Previous studies considered primarily hypothetical examples or small size networks and did not test the stability and suitability to real large scale networks (Santos & Haimes, 2004; Stapelberg, 2011; Wu et al., 2014; Laucelli and Giustolisi, 2014).

## **1.4 Objectives and Motivation**

The paradigm in asset management now is shifting from targeting a responsive policy to proactive policy with focus on integrated infrastructure management (Tushith and Moselhi, 2012; Osman et al., 2012). As mentioned early, most interdependencies models and vulnerability models were introduced primarily to cope with the disaster management. Therefore, the main objective of this research is to present a computational framework for optimizing intervention policies for integrated civil infrastructure

networks considering spatial and functional interdependencies. This can be achieved by a number of sub-objectives:

- 1- Study how infrastructure spatial and functional interdependencies can be modeled and incorporated into the framework of asset management. Capturing spatial and functional interdependent assets (bundles) is important for directing the analysis towards the most vulnerable parts of the infrastructure networks that can rapidly affect the functionality of other neighboring infrastructure systems.
- 2- Understand the effect of interdependency on the vulnerability assessment by recognizing various factors that control the rating of assets' vulnerability. Operation and maintenance reports were not utilized by other researchers in asset management to understand how assets become susceptible to failures based on their interdependencies.
- 3- Explore various computational models that can be incorporated for modeling vulnerability of interdependent assets. As highlighted in the problem statement, data availability was a major challenge to other researchers. This research will explore three models to handle limitations identified in previous vulnerability models such as 1) reliable historical data availability, 2) experts availability, and 3) ambiguity in collected judgments of experts.
- 4- Develop an automated DSS to optimize intervention policies at bundle and network levels in an effort to decrease vulnerability of water, sewer and road systems and cope with budget constraints. Intervention policies are selected to maximize the overall satisfaction of decision makers, considering interdependent assets' condition, vulnerability and level of service (LOS).

## 1.5 Research Framework Overview

The proposed research framework consists of three computational models as shown in Figure 1-1 and described below:

- 1- Literature review: the literature review focused on four topics: 1) interdependency assessment, 2) vulnerability assessment, 3) simulation models and 4) optimization and learning algorithms. This comprehensive literature review was used to; 1) identify current research gaps, 2) identify factors and models utilized by other researchers to assess vulnerability of interdependent assets and 3) select the most suitable research methods for achieving the above stated objective.
- 2- Data Collection: Two data sets of water, sewer and road infrastructure networks obtained from City of London, Ontario and City of Hamilton were analyzed. These datasets were analyzed not only to understand current practices of asset management but also to structure and develop the proposed models. The operation and maintenance reports were examined to extract factors influencing vulnerability of interdependent assets. The identified factors from the operation and maintenance reports of the two datasets are added to the identified factors from the literature and utilized as an input for the vulnerability model.
- 3- Interdependency assessment model: This model captures spatially and functionally interdependent assets using two modules: 1) spatial module, and 2) functional module. The spatial module utilizes ArcGIS geoprocessing tools in determining geographically interdependent assets.

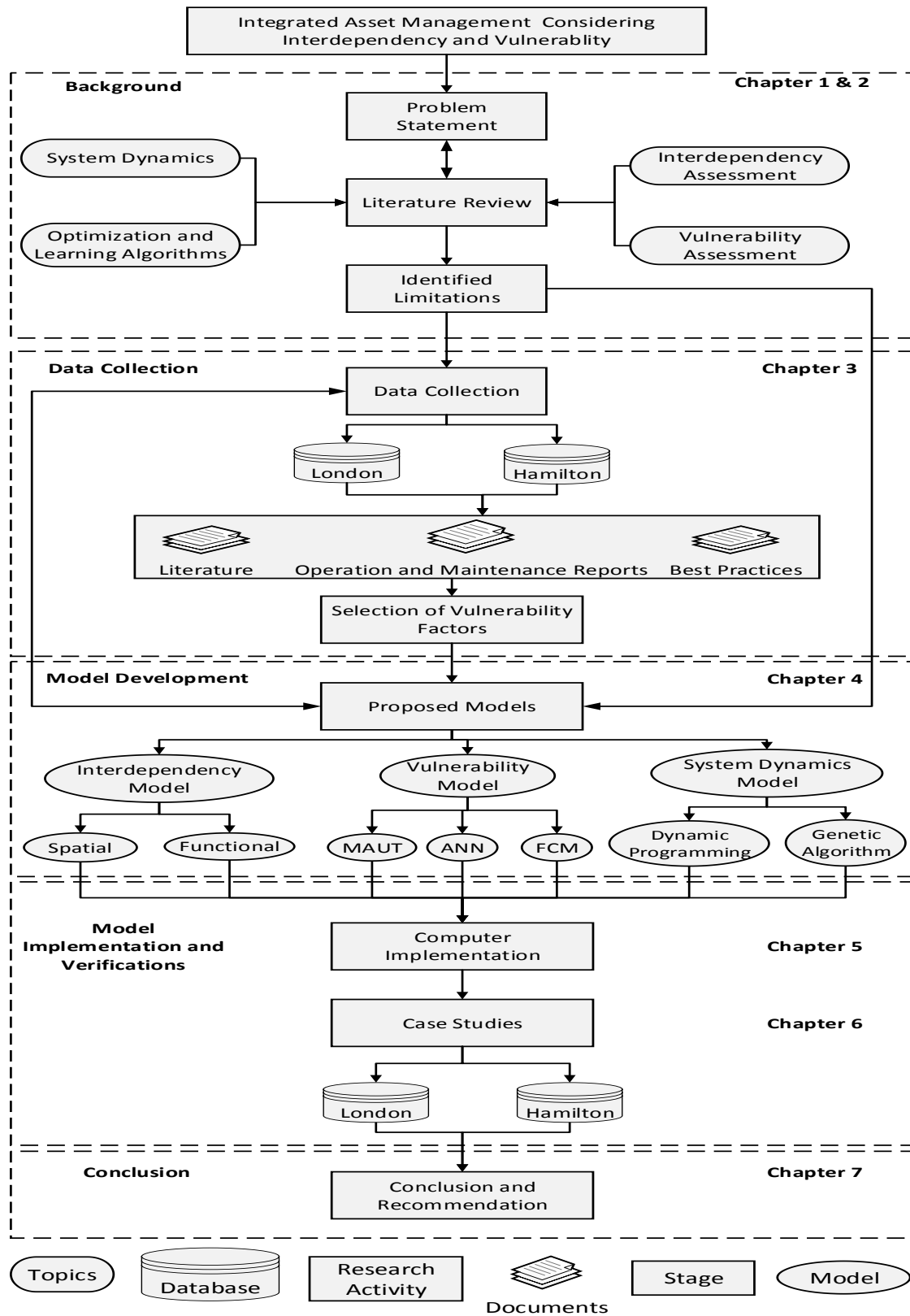


Figure 1-1 Research framework overview

The spatial module encapsulates the interdependent assets in a set of new layers and a new generated database containing characteristics of such interdependencies. On the other hand, the functional module employs principles of graph theory in determining an asset's degree of connectivity with its neighboring assets. The functional module will aid in recognizing the likely influence of an asset failure on its neighboring assets' performance.

- 4- Vulnerability assessment model: three computational models are investigated to assess vulnerability of interdependent assets; 1) Multi attribute utility theory (MAUT), 2) Artificial neural networks (ANN) and 3) Fuzzy c-mean (FCM). While Ezell (2005) used MAUT to rate vulnerability of water assets, Ezell (2005) ignored interdependencies effect on vulnerability assessment. Also, the performance of the MAUT model against other artificial intelligence models such as ANN and FCM was not benchmarked. The MAUT model utilizes judgments elicited from experts to construct utility functions for rating vulnerability of interdependent assets. However, the MAUT model suffers from the following; 1) experts don't necessarily understand or capture all observed patterns that can be found in each dataset, 2) subjectivity in estimating weights of selected MAUT factors and 3) ambiguity in rating vulnerability of interdependent assets due to collected judgements of experts. The ANN model is a data driven technique requiring less involvement from experts and is capable of capturing all observed patterns that can be found in each dataset. On the other



hand, the FCM model considers ambiguity that exists in rating vulnerability of interdependent assets due to collected experts' judgement.

5- System dynamics model: SD aids in understanding the behavior of complex systems at strategic level over time through causal feedback loops and stocks flow (Sterman, 2000). The system dynamics is utilized because; 1) it can represent nonlinear and history dependent systems (Osman et al., 2012), 2) causal feedback loops can be used to represent complex interactions on a strategic level among interdependent systems (Arboleda et al., 2010). The SD model is used to find optimal intervention policies at bundle level and network level respectively using two algorithms;

- I. Dynamic programming algorithm: The dynamic programming is an exact solution algorithm and is utilized at bundle level for finding and ranking the available intervention policies. The objective of this algorithm is to maximize the total satisfaction of decision makers gained by applying intervention policies at bundle level. The dynamic programming algorithm evaluates all the possible intervention policies and ranks the top ten policies based on the above stated objective considering condition, LOS and vulnerability constraints.
- II. Single objective genetic algorithm: The genetic algorithm is a near optimal solution algorithm and is deployed to find a near optimal policy at the network level considering the ranked policies identified by the dynamic programming algorithm. The single objective genetic algorithm (SOGA) is modified by; 1) integrating a query based filtering function

into the SOGA to cluster similar bundles, 2) dynamic memory to store worst solutions to prevent the regeneration of such solutions in next iterations, and 3) modifying the behavior of the mutation function to improve the convergence rate of the genetic algorithm. The system dynamics model is implemented using C#.

The general research methodology is shown in Figure 1-1. The details of the research framework and its proposed models are discussed in Chapter 4 and Chapter 5.

## **1.6 Thesis Organization**

The thesis consists of seven chapters and four appendices. The literature review is presented in Chapter 2. The review covers the topics of interdependency assessment, vulnerability assessment, simulation models, and optimization and learning algorithms. The listed topics are reviewed with a focus on how they reflect upon the developed models. Summary of the limitations and gaps in existing methods are presented at the end of this chapter as well. Chapter 3 begins by presenting an overview of the two datasets used to develop and test the proposed research framework. A detailed analysis is performed utilizing the operation and maintenance reports of water, sewer and road assets. Factors affecting asset's vulnerability are extracted. Chapter 4 describes the developed research framework and its proposed models. Chapter 5 covers the computer implementation of the developed research framework. It covers the designed database, classes, use-cases, sequence diagram and snapshots from its Graphical User Interface (GUI). In Chapter 6, two case studies are analyzed to demonstrate the potential benefits of applying the developed research framework. Chapter 7 highlights contributions and

limitations of the developments made in the thesis along with suggested future research work.

## **Chapter 2 : LITERATURE REVIEW**

### **2.1 Introduction**

Current asset management practices separate infrastructure networks into isolated layers ignoring their spatial and functional interdependencies with surrounding networks. For instance, consider a bridge with a gas pipeline attached to its deck, any failure in that bridge will probably compromise the functionality of parts of the gas network and the road network as well. Therefore, interdependency assessment facilitates identification of possibly interdependent assets, while vulnerability assessment aids in identifying their likely susceptibility to failures based on such interdependencies. The study of interdependency and vulnerability assessment was advanced in the last decade to provide decision makers with tools for judging systems performance mainly for disaster management applications. Terrorist attacks and natural hazards have amplified the importance of being equipped with DSS that encapsulate vulnerability assessment of infrastructure networks based on their interdependencies with neighbouring networks (Khan et al., 2010).

In current asset management practices, modeling of spatial and functional interdependencies and their impact on vulnerability of civil infrastructure networks is not considered (Moselhi et al, 2005; Wu et al., 2014). As will be shown later in this chapter, vulnerability and interdependency modeling, primarily, targeted disaster management applications (Osorio et al., 2007; Ouyang et al., 2009; Karmakar et al., 2010; Eun et al, 2010). The majority of the reviewed models and DSS for vulnerability assessment were designed and implemented ignoring the underlying spatial and/or

functional interdependencies that exist between civil infrastructure networks. Also, there is a lack of computational models to optimize intervention policies for interdependent infrastructure networks both on the bundle level (two or three interdependent assets) and networks level.

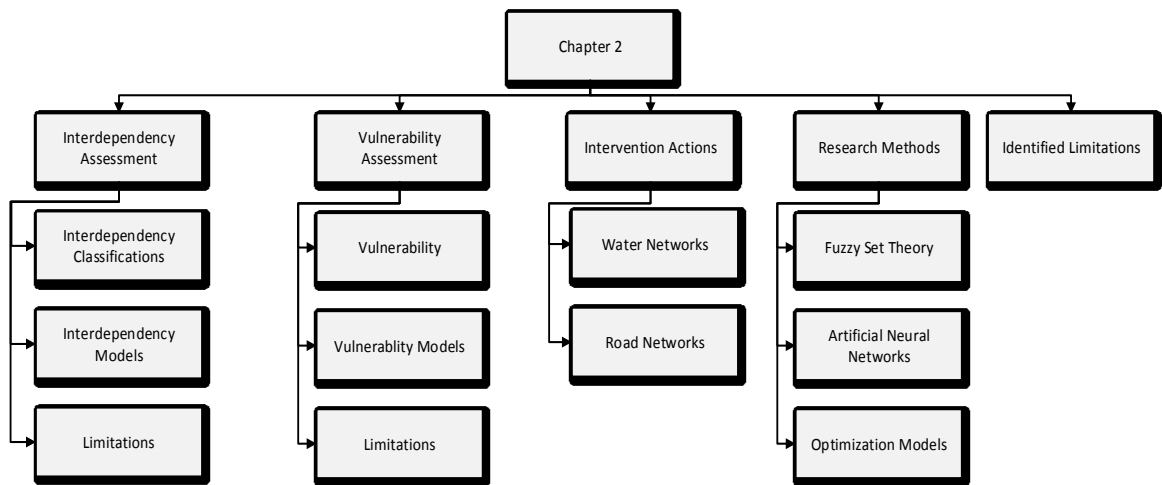


Figure 2-1 Chapter 2 overview

The literature review starts with discussing interdependency assessment, its classifications and models. The interdependency assessment models are classified into: 1) spatial interdependency models, 2) functional interdependency models and 3) economic interdependency models. Vulnerability assessment models are categorized into: 1) models overlooking interdependencies and 2) models considering interdependencies. The current state of the art of vulnerability assessment models is discussed and its limitations are identified as well. Available intervention actions to overcome the likely vulnerability of water, sewer and road assets are also covered. Subsequently, fuzzy set theory, artificial neural networks and optimization models are reviewed comprehensively as research methods that were utilized later in the research

framework chapter. Finally, the chapter concludes with a summary of identified limitations in previous research efforts. Figure 2-1 provides an overview of the topics covered in this chapter.

## **2.2 Infrastructure Interdependency**

As mentioned previously, interdependency assessment facilitates the identification of possibly interdependent assets and hence aids in identifying their likely susceptibility to failures in neighboring assets. Researchers tried to study and classify various types of interdependencies among civil infrastructure networks for applications in different contexts such as natural disaster management and response to terrorist attacks. The following subsections extract these classifications and illustrate how some of these classifications were modeled.

### **2.2.1 Interdependency Classifications**

Rinaldi, et al. (2001) classified infrastructure interdependencies as being one of four types: physical, cyber, geographic or logical. Physical interdependency means that the physical output of one infrastructure is the physical input to another infrastructure. Cyber interdependencies occur when infrastructure networks are being connected via information links and this type of interdependency is relatively new and is a result of advanced computerization and networking. Geographical interdependency means that two infrastructure assets impact one another because of geospatial proximity. Events like explosion or fire could create correlated disturbances in these geographically interdependent infrastructures. Logical interdependency means that the state of one infrastructure depends on the state of another infrastructure, usually via human decisions and actions. For example, lowering gas price may increase the availability of gasoline

in the market, increase cars purchases and cause traffic congestion. In this case, the logical interdependency between the petroleum and transportation infrastructure networks is due to macro-economic principles and not as result of a physical process.

A study developed by Dudenhoeffer et al. (2006) used a slightly expanded taxonomy where the categorization classifies the following types of relationships into: physical, informational, geospatial, policy/procedural and social interdependency. Physical and geospatial interdependencies definitions are similar to the definitions proposed by Rinalde et al. (2001). Informational interdependency defined as informational or control requirements between components. For instance, a loss of the SCADA system, supervisory control and data acquisition, will not by itself shut down the grid, but the ability to remotely monitor and operate the breakers is lost. Likewise, this relationship may represent a piece of information or intelligence flowing from a node that supports a decision process elsewhere. On the other hand, policy/procedural interdependency is due to policy or procedure that relates the state in one infrastructure sector to another infrastructure sector. For example, after the terrorist attacks of 2001 on the World Trade Towers, all U.S. air transportations were halted for more than 24 hours, and commercial flights were not resumed until three to four days. Social interdependency is the influence that an infrastructure component may have on the community such as public opinion, public confidence, fear, and cultural issues. Even if no physical linkage or relationship exists, consequences from events in one infrastructure may impact other infrastructures.

Earl et al. (2004) classified infrastructure interdependency into five min categories: input, mutual, co-located, shared and exclusive dependency. Input

interdependency depicts that the infrastructure requires input of one or more services from another infrastructure in order to operate. For example, the reliance of components in many infrastructure systems on power generators like pumps for water networks. Mutual interdependency means that two or more infrastructure assets are functionally interdependent upon each other. An example of mutual interdependency for two infrastructures occurs when an output of infrastructure A is an input to infrastructure B, and an output of infrastructure B is an input to infrastructure A (Earl et al., 2004). This could be a compressor in a natural gas system requiring power to operate and the generating facility that generates the power relies on the natural gas for fuel. Co-located interdependency definition is similar to the geospatial interdependency definitions presented by Rinalde et al. (2001) and Dudenhoefter et al. (2006) explained earlier. Shared interdependency occurs when physical components or activities of an infrastructure used in providing two or more services are shared. For example, streets are used by the transit system and by emergency services, two services sharing one infrastructure component. Exclusive interdependency is basically only one of two or more services can be provided by an infrastructure component at a time. An example of this can be drawn from the World Trade Center attack when some streets were made available only to emergency vehicles; private and transit vehicles were barred from using these areas (Earl et al., 2004).

### **2.2.2 Interdependency Models**

Generally, infrastructure interdependency modeling can be categorized into spatial, functional and economical models. Spatial interdependency models were utilized to encapsulate assets that are co-located in the XYZ planes (Tushith and



Moselhi, 2012; Shehata, 2013). Tushith and Moselhi (2012) deployed the geoprocessing toolbox of ArcGIS to encapsulate spatially interdependent water, sewer and road assets. The authors used the proposed model to quantify the extent of spatial overlap between two asset classes in order to determine the most suitable intervention based on the asset driving the rehabilitation. However, the authors chose not to address functional interdependencies among civil infrastructure assets and didn't consider their effect along with spatial interdependencies on increasing or decreasing assets' vulnerability. Shehata (2013) also utilized geoprocessing toolbox of ArcGIS to encapsulate spatially interdependent water, sewer and road assets for risk assessment. Shehata's (2013) model also shared the same limitations of Tushith and Moselhi's model (2012).

Functional interdependency models abstract each network functionality using graph theory principles and assess its interdependency using parameters such as degree of vertices, average shortest path and the clustering coefficient (Crucittia et al., 2003; Gesara and Osorio, 2010; Wu et al., 2014). In graph theory models, a network can be visualized as finite collection of entities together with a specified pattern of relationships among these entities. A generic network is represented by a graph  $G$  with  $N$  vertices (nodes) and  $K$  edges (arcs, links or connections) (Crucittia et al., 2003). Such a graph is described by the so-called adjacency matrix ( $A$ ) (also called connection matrix) as shown in Figure 2-2. Adjacency matrix ( $A$ ) is  $N$  by  $N$  symmetric matrix, whose entry  $a_{ij}$  is 1 if there is an edge joining vertex  $i$  to vertex  $j$ , and 0 otherwise. An important characteristic of graph  $G$  is the degree of a generic vertex  $V$ , the number of edges  $K$  incident with vertex  $V_i$  or in other words the number of neighbors of  $i$ . In the above figure,  $K = \sum_i K_i / 2$  because each link is counted twice, and the average value of  $k_i$  is

$\langle k \rangle = 2K/N$ . This implies that higher average degree of G implies stronger interconnectivity of the nodes in the network.

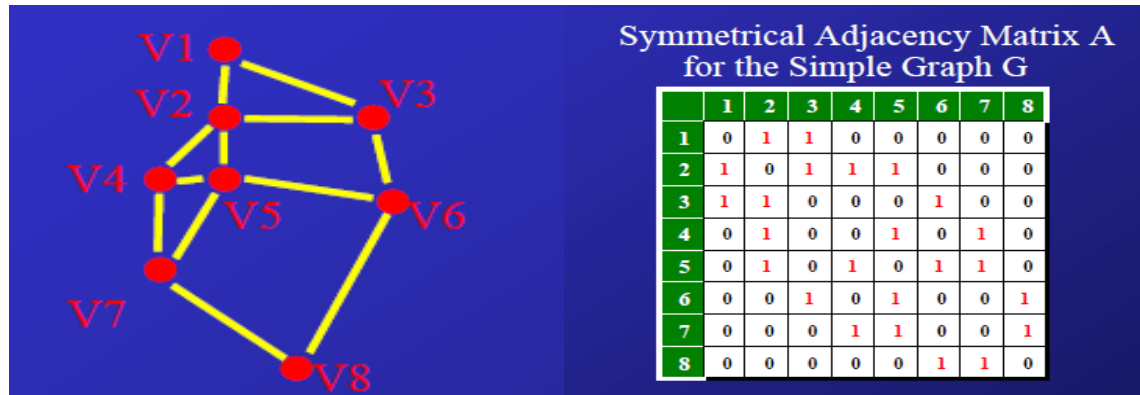


Figure 2-2 Network with adjacency matrix (adapted from Crucittia et al., 2003)

Another property is the characteristic path length (L) of a network which is the shortest path length between two nodes averaged over all pairs of nodes and is given by:

$$L = \frac{\sum_i \sum_j L_{i,j}}{N(N-1)} \dots \dots \dots \text{Equation 2-1}$$

Where  $L_{i,j}$  the shortest distance between any two nodes, N is is the number of nodes in the graph.

As the characteristic path length increases, the network is almost in liner chain and as the characteristic path length decreases, the network can be said to be in compact form. The third measure is the clustering coefficient C which is the ratio between the total number of the edges ( $e_i$ ) actually connecting its nearest neighbors to the  $i^{\text{th}}$  node and the total number of all possible edges between all these nearest neighbors ( $k_i(k_i-1)/2$ ); if the  $i^{\text{th}}$  vertex has  $k_i$  neighbors then the clustering coefficient is given by

$$C_i = \frac{2e_i}{K_i(K_i-1)} \dots \dots \dots \text{Equation 2-2}$$

Where  $e_i$  is the total number of edges actually connecting the  $i^{\text{th}}$  node's nearest neighbors,  $K_i$  is the vertex degree

Hence, the clustering coefficient of a network is the average of its all individual  $C_i$ .

$$C = \frac{\sum_i C_i}{N} \dots\dots\dots \text{Equation 2-3}$$

Where  $N$  is the number of nodes in the graph.

The above stated functional interdependency models overlooked the effect of assets' condition on functional interdependency and such models were also designed for disaster management applications. These models were focusing on capturing functionally interdependent assets but did not attempt at allocating intervention actions based on the captured interdependencies.

Economic interdependency models were implemented to assess the effect of natural or man-made hazards on interdependent networks by utilizing either input/output analysis (IO) (Haimes et al., 2001; Haimes and Jiang, 2001; Santos and Haimes, 2004) or simulation techniques (Macal and Macal, 2005; Dudenhoefter et al., 2006). Input-Output (IO) economic analysis was introduced by Wassily Leontief in the early 1930s, but adapted later to model interdependent infrastructure systems using the same principles for interrelated economic sectors interactions. Any economic system is assumed to consist of a group of  $n$  interacting sectors or industries and each industry produces one product (commodity). A given industry requires labor, input from the outside, and also goods from interacting industries. Therefore, each industry must

produce enough goods to meet both interacting demands from other industries in the group plus external demands (e.g., foreign trade and industries outside the group). A static (equilibrium-competitive) economy, with constant coefficients for a fixed unit of time (1 year), is assumed (Haimes et al., 2001). Using the early Leontief IO analysis, Haimes et al. (2001) developed the linear input-output inoperability model (IIM) to study the inoperability of interdependent networks. The developed model employed the basic principle shown in Equation 2-4 for economic interdependency between different sectors.

$$X_i = \sum_j a_{ij} \cdot X_j + C_i \text{ for } \forall i \dots \dots \dots \text{Equation 2-4}$$

Where  $X_i$  : The total production output from the industry,  $I$ ,  $a_{ij}$ : The Leontief technical coefficient, the ratio of inputs of industry  $i$  to industry  $j$ , in terms of the production requirements of industry  $j$  and  $C_i$  : The portion of industry  $i$ 's final production for end user consumption.

From infrastructure perspective, this equation can be interpreted as risk of inoperability. In this model,  $x_j$  is the overall risk of inoperability experienced by infrastructure  $j$ , and is a measure of both degree of inoperability and its probability.  $a_{ij}$  is the probability of inoperability that the  $j^{\text{th}}$  infrastructure contributes to the  $i^{\text{th}}$  infrastructure due to their interdependency, and  $c_j$  is the additional risk of inoperability that is inherent in the complexity of the  $j^{\text{th}}$  infrastructure.

For example, in a two system model where failure of subsystem 2 leads subsystem 1 to be 80% inoperable, and a failure of system 1 leads subsystem 2 to be 20% inoperable, the effects of functionality loss due to an external perturbation can be

calculated by solving the Leontief equation adapted for infrastructures (Haimes and Jiang, 2001). Specifically, interdependent effects can amplify a 60% loss of performance from external perturbations in subsystem 2 to a 57% inoperability of subsystem 1, and 71% inoperability of subsystem 2 according to the IIM approach as shown in Figure 2-3.

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 0 & 0.8 \\ 0.2 & 0 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 0 \\ 0.6 \end{pmatrix} = \begin{pmatrix} 0.8x_2 \\ 0.2x_1 + 0.6 \end{pmatrix}$$

Figure 2-3 I/O model for two sub-systems (Haimes & Jiang, 2001)

Santos and Haimes (2004) then created the demand-reduction model to complement the economic analysis for interdependent infrastructure systems. This demand-reduction model utilized both geographic and functional decomposition methods to allow for a more accurate analysis of specific geographic regions and the breakdown of large-scale systems into smaller subsystems (Santos & Haimes, 2004). The above cited IO models suffers from the following; 1) the need for extensive data mining and experts opinions in order to estimate the required inputs, 2) being designed and implemented for disaster management applications and 3) the lack of computational models to optimize intervention actions based on the captured degree of economical interdependency.

On the other hand, simulation models aim to simulate infrastructure networks through agent based modeling (ABM) or system dynamics (SD) to encapsulate the interactions between various networks and users as well with the adoption of graph theory principles (Dudenhoeffer et al., 2006). In agent based simulations, infrastructure networks are modeled as complex adaptive systems (CAS) composed of agents where each agent has a specific set of characteristics. An agent is a singular piece of code with

a specific physical location, function, and memory of past interactions and behaviors. A fundamental element of CAS and agent based modeling (ABM) is the emergence of agents' behaviors when agents are brought together to interact in a single environment. Different agents can be modeled at varying degrees of granularity based on the intended level of resolution modeling (Macal & Macal, 2005). Several ABM tools have been released recently to encapsulate economic interdependencies among civil infrastructure.

Researchers at Sandia National Laboratories have developed agent based economic laboratory (N-ABLE) for analyzing economic factors' effect on interdependent infrastructure assets (Macal & Macal, 2005). N-ABLE is a simulation environment in which a set of agents simulate real-world manufacturing firms, government agencies, and households. N-ABLE was developed using C++ to run on a single-processor computer. Each agent behaves the way its counterpart in the real world would behave, as the simulation traces the agent's daily actions (e.g., buying commodities, selling commodities, paying for commodities by check...etc.). This modeling approach is well suited for investigating the behavior of complex, nonlinear stochastic systems like the economy. Agents start each time increment making decisions much like their real-life counterparts. Decisions on actions to take are based either on probabilities computed from actual microeconomic data or on results of learning models including genetic algorithms. These decisions include purchasing products, hiring workers, selling bonds, collecting welfare payments, conducting open market operations, and others. Macroeconomic variables, such as gross domestic product, inflation, and the unemployment rate are computed as aggregate results of innumerable decisions by the individual economic agents.

Another ABM was developed by Idaho National Laboratory (INL), CIMS, to simulate economic interdependencies among infrastructure assets and the complex behaviors that can result. The key characteristic of the agent and the simulations is that each agent exists as an individual entity which maintains a state, senses input, and possesses rules of behavior that act upon the inputs and either modify the state or produce an output (Dudenhoeffer et al., 2006). The infrastructures networks within the simulation are modeled using graph theory and visualized using 3D objects. The model was introduced as a tool for infrastructure analysis supporting the ability to conduct “what if” scenario analysis. According to the authors, CIMS has been applied to evaluate infrastructure at the INL and has been used as a validation tool with other infrastructure interdependency modeling projects. Currently, CIMS is being evaluated by the Louisiana Recovery Authority for applications in Hurricane Katrina and Rita recovery and restoration activities (Dudenhoeffer et al., 2006).

System dynamics (SD) is an approach for understanding the behavior of complex systems over time and deploys internal feedback loops and time delays that affect the behavior of the entire system (Sterman, 2000). System dynamics is unique from other approaches in studying complex systems by considering the effect of feedback loops, stocks and flows and describes how even seemingly simple systems display baffling nonlinearity. Stapelberg (2011) presented a conceptual system dynamic model that can be used to model different infrastructure types as shown in Figure 2-4.

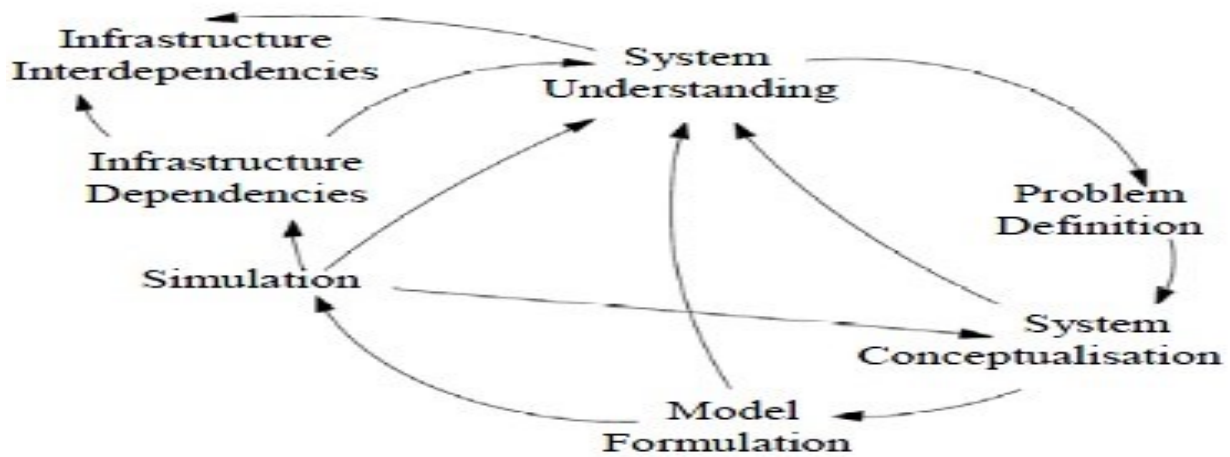


Figure 2-4 General framework for Infrastructure Interdependency using SD (Stapelberg, 2011)

Afterwards, the model developed by Stapelberg (2011) is used to encapsulate the system reaction due to certain type of hazards. In this model, the author differentiates between two concepts; system dependency and system interdependency. The system dependency means that system A depends on system B but system B is independent from system A. Interdependency means both systems depends on each other. Feedback is deployed to facilitate the visualization of certain physical or functional failure of systems elements on other systems. For instance, in water industry, as the demands of different sectors increases and users for water usage, the overall usage rate will increase as shown in Figure 2-5. As such, the water supply rate should be increased to cope with such effect which is controlled by government regulation and policies. The supply can be increased by capital investment in constructing new infrastructure elements or enhancing the capacity of existing infrastructure. These investments however are controlled by the economy and financial capability of the State at time of the analysis.





### **2.2.3 Limitations of Interdependency Models**

The limitations of the above stated interdependency models can be summarized as the following:

- 1- For spatial interdependency models (Tushith and Moselhi, 2012 and Shehata 2013): these models overlook functional interdependencies among civil infrastructure assets and don't consider their effect along with spatial interdependencies on increasing or decreasing assets' vulnerability.
- 2- For functional interdependency models (Crucittia et al., 2003; Gesara and Osorio, 2010; Wu et al., 2014):
  - a. These models overlook the effect of assets' condition on functional interdependency.
  - b. Such models are designed and implemented for disaster management applications.
  - c. These models are focusing on capturing functional interdependent assets but do not attempt at allocating intervention actions based on the captured interdependencies.
- 3- For economical interdepency models: in this category, two types of models were discussed; IO models (Haines et al., 2001; Haines and Jiang 2001; Santos and Haines, 2004) and simulation models (Macal & Macal, 2005, Dudenhoefter et al., 2006; Stapelberg, 2011). The above sited IO models suffer from the following;
  - a. The need for extensive data mining and experts opinions in order to estimate the required inputs.

- b. Such models were designed and implemented for disaster management applications.
- c. Lack of computational models to optimize intervention actions based on the captured degree of economical interdependency.

On the other hand, the simulation models suffer from the following:

- a) The majority of these models are either conceptual or still under development and thus such models need further enhancements and more verification and validation,
- b) These models are concerned mainly with economic interdependency among civil infrastructure networks for disaster management applications.
- c) The above stated models also overlook vulnerability assessment from the economic analysis.
- d) These models were mainly utilized to experiment with what-if scenarios for intervention at the bundle level only.
- e) These models are not supplemented with optimization techniques to allocate the intervention actions to decrease the need to extensive experts' knowledge.

## **2.3 Vulnerability Assessment**

Vulnerability assessment measures an asset's degree of susceptibility for structural and/or functional failures triggered by failure of these functions in neighboring assets. In the past decade, researchers tried to assess the vulnerability of infrastructure networks in different contexts (i.e. social, engineering, economical ...etc.). The

following part of the literature review focuses on the current state of the art for vulnerability assessment models in engineering applications and more specifically in disaster management and asset management. The following two subsections extract vulnerability definitions, classifications and illustrate how some of these classifications were modeled.

### **2.3.1 Vulnerability Classification**

Vulnerability has various definitions based on the perspective of the analyst. Vulnerability may be defined as “The extent to which a community, structure, services or geographic area is likely to be damaged or disrupted by the impact of particular hazard, on account of their nature, construction and proximity to hazardous terrains or a disaster prone area.” (Khan et al., 2011). Blaikie et al. (1994) defines the vulnerability as “the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard”. The National Oceanic and Atmospheric Administration (NOAA, 2002) views vulnerability as: “susceptibility of resources to negative impacts from hazard events”.

Vulnerabilities have different classifications also based on the field and the purpose of the study. For instance, Khan et al. (2011) categorized vulnerabilities into physical and socio-economic vulnerability to analyze natural disaster impacts. Physical vulnerability includes notions of whom and what may be damaged or destroyed by natural hazard such as earthquakes or floods. It is based on the physical condition of people and other elements at risk (i.e. buildings, infrastructure ...etc.) based on their proximity to hazard and nature of the hazard. On the other hand, socio-economic vulnerability may be related to the population affected by a specific hazard in terms of

tangible and intangible losses based on the demographic characteristics of the impacted area. For instance, people who are considered as low income and living in coastal areas may favor construction of vulnerable types of housing such as wood housing and hence they are generally at risk of losing their shelters whenever there is strong wind or cyclone. Ouyang et al. (2009) classified the vulnerability of interdependent infrastructures into two types of vulnerability: structural vulnerability and functional vulnerability. The reason for such classification was to consider the vulnerability of interdependent infrastructure assets under terrorist attacks.

### **2.3.2 Vulnerability Assessment Models**

Vulnerability assessment is systematic procedure for assessing susceptibility of infrastructure networks based on captured interdependencies among neighboring assets. In disaster management, the goal of performing the vulnerability assessment exercise is to determine the adequacy of security measures, identify security deficiencies, evaluate security alternatives, and verify the adequacy of such measures after implementation (Earl et al., 2004). A disaster is a result of a combination of hazard, vulnerability and insufficient capacity or measures to reduce the potential chances of risk. As the degree of vulnerability of an asset increases, the hazard impacts are increasing causing economic and social damages and disruption. Therefore, risk assessment is a function of hazard and vulnerability and measures the possibility of future harm based on the present state. Each system component is being assessed to evaluate the susceptibility of the various system components to a certain hazard.

Subsequently, these vulnerable components are being evaluated based on the vulnerability consequences (social, economic, political etc.) along with the likelihood of such hazard. Such evaluation will form a crisp idea about the system risk characteristics due to hazards and current system capacity. Generally, the vulnerability assessment models can be classified into; models overlooking interdependencies (Ezell, 2005; Karmakar et al., 2010; Flax et al., 2003; Wu et al., 2014; Laucelli and Giustolisi, 2014) and models considering interdependencies (Ouyang et al., 2009; Arboleda et al., 2010; Eun et al., 2010 ).

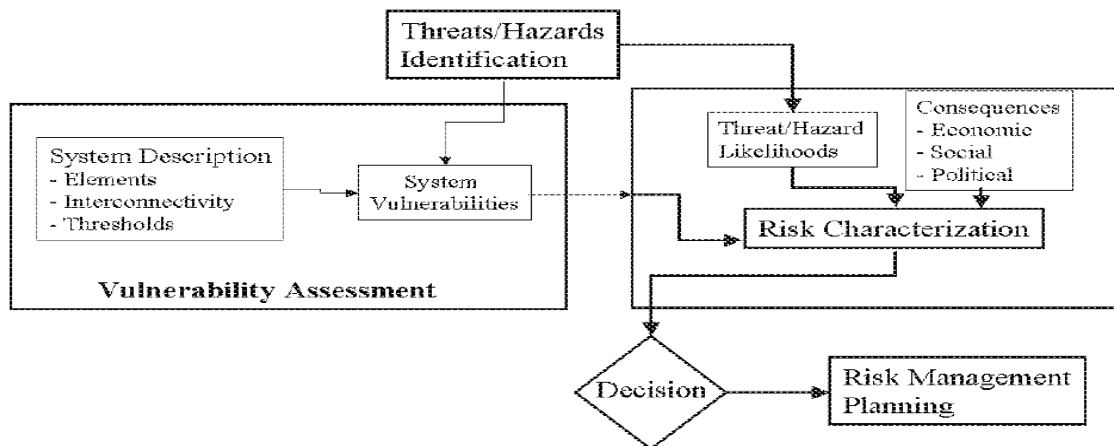


Figure 2-6 Vulnerability assessment and risk assessment process (Baker, 2003)

For vulnerability models overlooking interdependencies, Karmakar et al. (2010) presented a study for vulnerability analysis of infrastructure due to floods by considering four types of infrastructure attributes: 1) physical, 2) economic, 3) infrastructure and 4) social. Such attributes are evaluated individually using a Geographic Information System (GIS) environment and the impact on infrastructure vulnerability is estimated based on its effect on critical facilities, emergency service stations and bridges. The components of vulnerability are combined to determine an overall vulnerability to flood. The values of probability of occurrence of flood, vulnerability to flood, and exposures

of land use and soil type to flood are used to finally compute flood risk at different locations in a watershed. The objectives of this model were to provide a DSS to: develop land development plans and land use zoning; plan emergency response strategies; select waste disposal sites and prepare infrastructure budgetary decisions. Flood risk is a combination of potential damage and probability of flooding. In this study, flood risk is the product of probability of occurrence ( $P_e$ ), vulnerability to flood ( $V$ ), and exposures of land use ( $E_{Land}$ ) and soil permeability ( $E_{Soil}$ ) as shown:

$$\text{Flood Risk} = P_e * V * E \dots\dots\dots \text{Equation 2-5}$$

The model framework is shown in Figure 2-7 where the four vulnerability factors are assessed separately. For instance, the physical vulnerability is assessed by the structural vulnerability of the assets or facilities during the flooding. On the other hand, for social vulnerability in a specific area, the income, ethnicity, household structure...etc. are used to measure the overall impact of a flood on a certain area.

Economic vulnerability includes flood damage indicators which can be expressed in monetary terms. Infrastructure vulnerability includes civil structure such as road networks, railways, and road bridges. Infrastructure components are important to the movement of population, communications, and safety. Their inundation impedes traffic and hinders communications, increasing stress in the exposed population. Inundation may also block important emergency routes and cause physical damage to roads. Afterwards, vulnerability indices along hazard probability of occurrence and Impact of exposure will be used to see the overall vulnerability index for certain region. Subsequently, such indices are visualized on digitized GIS map to different end users.

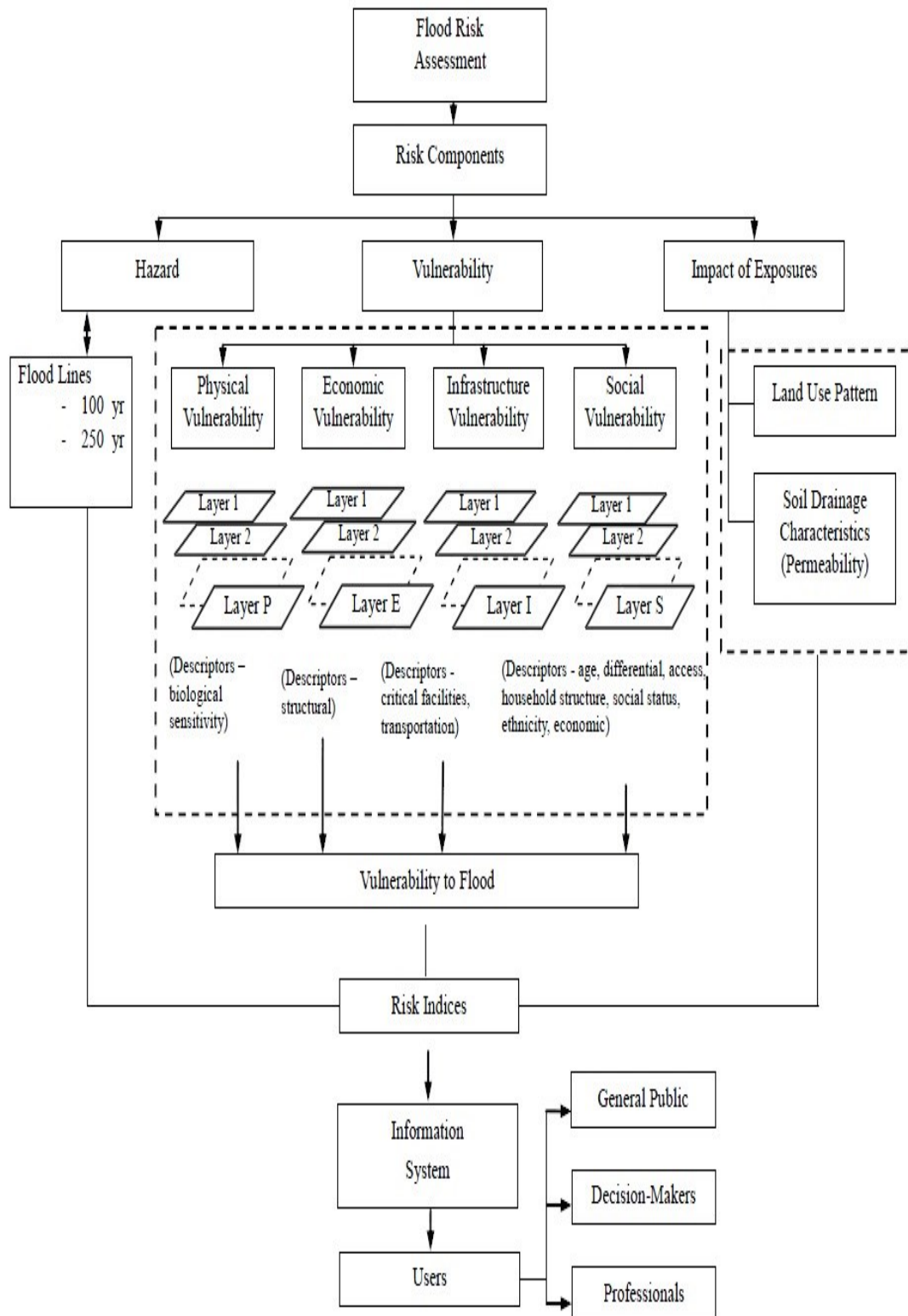


Figure 2-7 Framework for vulnerability and risk assessment (Karmakar, et al., 2010)



The Community vulnerability assessment tool (CVAT) is another tool for vulnerability assessment that overlooks interdependencies among civil infrastructure. The CVAT tool was designed by the National Oceanic and Atmospheric Administration's Coastal Services Center (Flax et al., 2003). CAVT was introduced to assist emergency managers and planners in their efforts to reduce hazard vulnerabilities through hazard mitigation, comprehensive land-use, and development planning. CVAT analysis results provide a baseline to prioritize mitigation measures and to evaluate the effectiveness of those measures over time. Prior to each analysis, hazard identification must be performed by the working group to formulate a general list of hazards (i.e. natural, manmade and technological). The outcome of this step will result in a prioritized list of hazards, based on the concerns and perceptions of the community. The CVAT model uses the following scoring equation to rate the vulnerability of an infrastructure:

$$\text{Vulnerability} = (\text{Frequency} + \text{Area Impact}) * \text{Potential Damage Magnitude}$$

.....Equation 2-6

Total Score for the frequency, area impact, and potential damage magnitude values are defined on a scale of numbers from 1 to 5, where 1 is low and 5 is high. This scoring system is subjective to facilitate the use of the tool for different users' types. The ArcGIS maps will be used later to identify vulnerabilities and mitigation options for a specific hazard. In the critical facilities analysis, the focus is on determining the vulnerabilities of key individual facilities, lifelines, or resources within the community. Critical facilities may include emergency shelters, schools, hospitals, public buildings, police stations, utilities ...etc., or those identified as critical by the working group. Because it is not usually feasible to conduct a structural and operational analysis for

every structure in a community, this step helps to prioritize which facilities are most vulnerable, so that individual assessments may be performed later.

Ezell (2005) proposed a model that requires experts' judgment to rate vulnerability of water networks using simple scoring method. The model considered four factors to rate the functional vulnerability of water assets. Wu et al. (2014) presented a model to calculate vulnerability of water channels considering three factors: channel connectivity, transportation efficiency and economic loss. The authors used analytical hierarchy process (AHP) with a hypothetical case study to assess vulnerability of water channels. Laucelli and Giustolisi (2014) presented a methodology to analyze vulnerability of water distribution networks for seismic events by using fragility curves and network topography in order to separate the network segments where failures may occur, using a hypothetical case study.

The above stated models for vulnerability assessment without considering interdependencies (Ezell, 2005; Karmakar et al., 2010; Flax et al., 2003; Wu et al., 2014; Laucelli and Giustolisi, 2014) have the following limitations:

- 1- The above cited methods are designed and implemented ignoring the underlying spatial and functional interdependencies that exist between water, sewer and road networks.
- 2- Vulnerability and interdependency modeling target, primarily, disaster management applications.
- 3- The majority of these models are subjective and require extensive involvement from the experts in rating vulnerability of infrastructure networks except for Laucelli and Giustolisi (2014).

- 4- These models do not present a systematic approach in allocation intervention actions for the likely vulnerable infrastructure networks on bundle and network level.

For vulnerability models considering interdependencies, Arboleda et al. (2010) presented a SD model to evaluate vulnerability of health care systems based on interdependencies with neighbouring civil infrastructure networks for disaster response plans. Physical damage to health care facilities or disruption of their operations or supply chains could prevent a full, effective response to a disaster and exacerbate the outcome of an emergency situation. In this study, three models (normal operations, response to a disruption, and restoration) are used to assess the level of interdependencies between the health care facility and the primary infrastructure systems linked to the facility (Arboleda et al., 2010). Arboleda et al. (2010) used optimization techniques to determine the unsatisfied demand in the major infrastructure systems and the impact of this shortage of resources on the operation of the hospital. A system dynamics simulation model is used as a tool to represent the operation of a health care facility, including the interaction between the different service areas (emergency room, intensive care unit, wards, operation room), the flow of patients within the facility, and the condition of the infrastructure systems that supply resources (i.e., water, power, medical supplies) to maintain the operation of the facility. The model objective was to assist in determining cost effective operational strategies in a health care facility in order to respond to a disaster event. The model was implemented using Vensim PLE software for SD (Arboleda et al., 2010).

Ouyang et al. (2009) introduced a methodological approach to comprehensively analyze the vulnerability of interdependent infrastructure networks (Figure 2-8). In this approach, two types of vulnerability were considered: structural vulnerability and functional vulnerability. The interdependent infrastructure topologies were generated based on geographical proximity. For this model, Vulnerability was related to attacks (manmade hazards) which decrease the efficiency of the infrastructures. Topology Extraction means converting the infrastructure drawings using graph theory principles to a graph  $G = \{V, E\}$  with  $N$  nodes,  $V = \{v_i\}$  is the set of vertices and  $E$  is the set of edges, denote  $d(v_i, v_j)$  by the shortest path lengths connecting two nodes in the network. Consequently, this extraction or digitizing is used to simulate the infrastructures structural and functional interdependency.

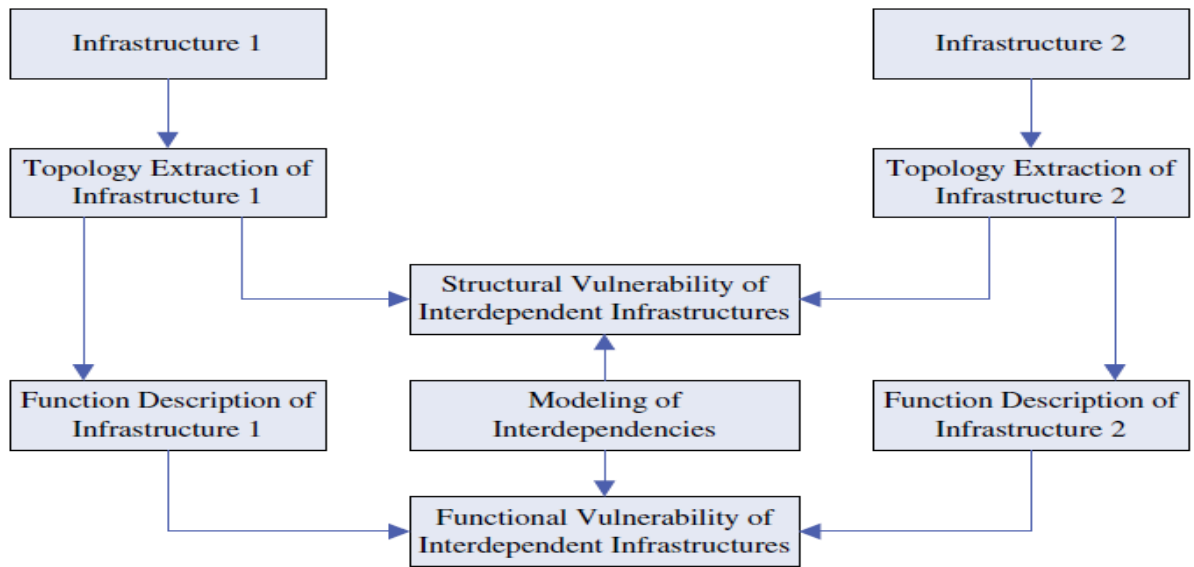


Figure 2-8 Vulnerability assessment model (Ouyang et al., 2009)

Eun et al. (2010) presented a decision support system (DSS) using Bayesian Network theory and System Dynamics (SD) method for vulnerability assessment of

critical infrastructure as shown in Figure 2-9. The objective of this model was to support emergency agencies and industries in preparing customized mitigation strategies and plans for preparedness, response, and recovery using the criticality and vulnerability analyses. The Bayesian Network theory was introduced to estimate the probability of failure of different infrastructures to different hazards. Vensim PLE software, was used as a tool for the simulation. There are three types of variables in the model: constant, auxiliary, and level. The sources of flood and other information (topographical conditions, water pressure ..., etc.) are examples of constant variables which provide basic information of the flood and the conditions of infrastructure as initial values as shown in Figure 2-9. The box nodes are all auxiliary variables except Diamond V which is a level variable. Auxiliary variables calculate the vulnerability by combining the values from constant variables and transfer the result to associated auxiliary and level variables.

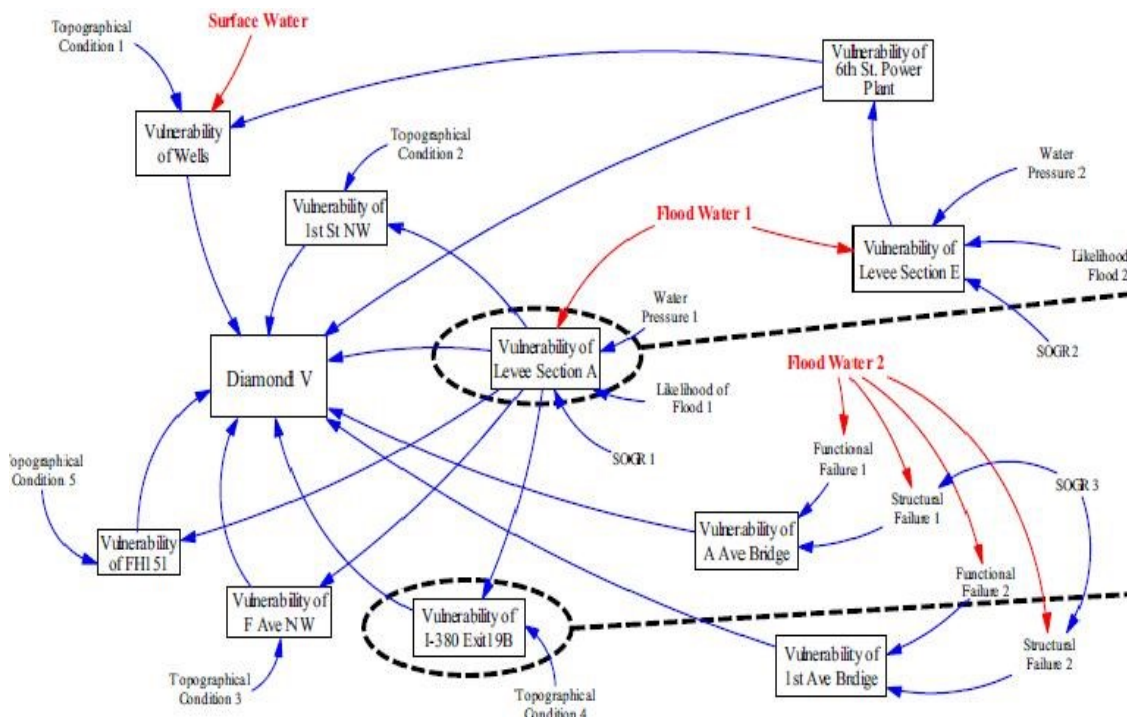


Figure 2-9 SD model for vulnerability assessment (Eun et al., 2010)

### **2.3.3 Limitations of Vulnerability Models**

The vulnerability models discussed in previous section suffer from the following:

- 1- For vulnerability models overlooking interdependencies (Ezell, 2005; Karmakar et al., 2010; Flax et al., 2003; Wu et al., 2014; Laucelli and Giustolisi, 2014):
  - a. The above cited methods are designed and implemented ignoring the underlying interdependencies among civil infrastructure networks.
  - b. Vulnerability modeling target, primarily, disaster management applications.
  - c. The majority of these models are subjective and required extensive involvement from the experts in rating vulnerability of infrastructure networks except for Laucelli and Giustolisi (2014).
  - d. These models don't present a systematic approach in allocation intervention actions for the likely vulnerable infrastructure assets on bundle and network level.
- 2- For vulnerability models considering interdependences (Ouyang et al., 2009; Arboleda et al., 2010; Eun et al., 2010 ):
  - a. When assessing spatial and functional vulnerability, these models ignore important factors like; asset condition, soil type, neighboring asset condition, customer types ...etc. These factors and others may have an effect on increasing or decreasing vulnerability of interdependent assets in asset management framework. Further effort

is needed in order to incorporate vulnerability assessment into the asset management cycle.

- b. The reviewed vulnerability models focus on mainly assessing vulnerability of interdependent assets however few of these models provided a framework for allocating intervention actions on bundle level only.
- c. These models focus on assessing one type of vulnerability (i.e. functional or structural or economic ...etc.) except for Ouyang et al. (2009). However, Ouyang et al. (2009) model is designed and implemented for disaster management application.

## **2.4 Intervention Actions**

### **2.4.1 Water and Sewer Networks**

Intervention practices aim at maintaining or improving the performance of buried infrastructures in terms of quality of service, hydraulic capacity and structural resiliency. All rehabilitation techniques make use of the pipe earthier as a part of the rehabilitated system (renovation) or as convenient for the new pipe (replacement). A hierarchy of maintenance operations can be identified such that failure to carry out work at one level will often lead to the need to carry out work at a higher and more expensive level at a later date. A simple hierarchy for sewer maintenance can be defined as follows by (InfraGuide (2003), Abbott (2005), Hastak, (2002)):

- Level 1 - Routine and periodic cleaning (pre-emptive), if this is not carried out it may lead to level 2 Maintenance requirements.

- Level 2 - Unblocking pipes (reactive),
- *Level 3* - Local repair and root control (pre-emptive with the need to be identified through sewer inspections). If this is not done it may lead to level 4 maintenance.
- Level 4 - Relining. Failure to reline when required could lead to collapse and the need to completely replace the pipe (level 5).
- Level 5 - Replacement.

In case of replacement, the operators have the chance to choose between open cut method and trenchless technologies. Open cut method Involves digging a trench along the proposed pipeline route, placing the pipe in the trench on a suitable bedding material, and then backfilling. This method is well documented, and most municipalities have good design and construction specifications for these types of projects (Infraguide, 2003). The installation of new replacement pipe should only be undertaken when the review of all alternate technologies has been completed and the open cut method is ranked as the best alternative. The benefits of such method according to InfraGuide (2003) are the following:

1. Completed with all new appurtenances.
2. The water and wastewater mains can be aligned to meet the needs of the local area.
3. The Water and wastewater service lines can be upgraded in material and diameter, and lowered to meet current standards.
4. Water and wastewater main sizing can be changed to meet current and future maximum day and fire flow requirements for water mains.



5. Other infrastructure can be rehabilitated or replaced at the same time, allowing for coordinated work and sharing of costs.

The disadvantages of such method according to InfraGuide (2003) are:

1. The cost of the open cut method can be substantial compared to some of the newer technologies.
2. The construction duration may be considerably longer than most trenchless technologies because of the amount of disturbance to other infrastructure and traffic, as well as the amount of reinstatement work required following the installation of the water and wastewater mains.
3. There are more safety concerns due to traffic issues on road right-of-ways, the number of excavations required, and the large, heavy equipment needed to perform the work.
4. There can be significant disturbance to other surface and buried infrastructure which may result in costly relocations.
5. Social and environmental costs of major open cut projects may be substantial during construction.

On the contrary, trenchless technologies are methodologies allowing new underground pipe routing with minimum disruption to the surrounding media i.e. (traffic, nearby utilities, building....etc.) (Abbott, 2005). Additionally, trenchless technologies can be installed to improve the hydraulic performance of certain parts of the networks or water quality levels for coping with customers' expectations (Hastak, 2002). Trenchless technologies are advanced over the conventional open-cut method in the following:

- Minimize traffic disruption (Abbott, 2005).
- Less exposed work site which results in improved construction safety (Hastak, 2002).
- Eliminates need for pavement restoration (Infraguide, 2003).
- Minimizes chance of disturbing existing utilities (Abbott, 2005).
- Minimizes damage to nearby buildings (InfraGuide, 2003).
- Less disruption to the public (noise, pollution, etc...) (Abbott, 2005).

Generally, trenchless technologies can be classified into trenchless construction methods and trenchless rehabilitation methods. Trenchless construction methods are deployed either to rout a new pipe into service or to replace an in-service pipe with fragile structural resiliency as shown in Figure 2-10.

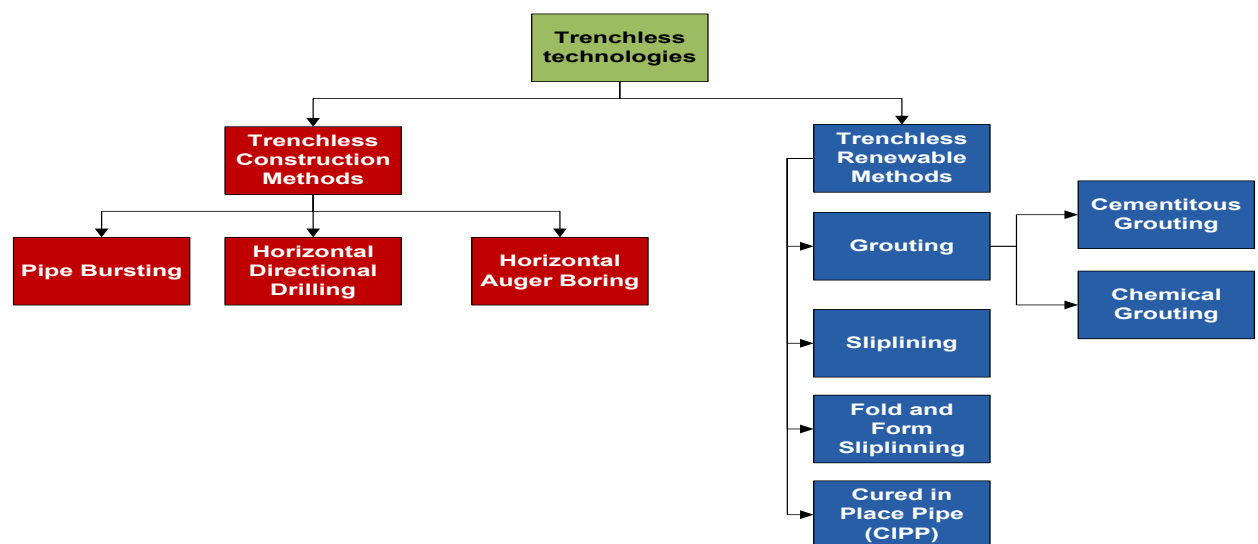


Figure 2-10 Trenchless technologies classifications

Essentially, trenchless renewable technologies are used to improve the hydraulic performance and decrease the structural deterioration of a pipeline. Infraguide (2003) determines a number of items that should be considered before selecting a rehabilitation or replacement technology for remedial action, those items can be articulated as follows:

1. Construction related issues, such as safety, operability, cost, and efficiency.
2. The size and duration of the contract. Smaller contracts may exclude some alternatives due to the cost of mobilizing specialized equipment and personnel. On contrary, major rehabilitation projects enlarge the analysis of alternatives for cost effective rehabilitation decisions.
3. The risk of undertaking (or not undertaking) the project: In this task, the focus is on environmental and construction concerns and what may adversely affect the project's objective.
4. Local availability of the various technologies: this inherently affects the projects in terms of mobilization costs and personal expertise related costs. Careful economic and engineering assessment should be conducted to balance between costs and benefits of such technique.
5. The depth of desired pipeline: this may limit the technologies available to rehabilitate or replace for certain water and wastewater main.
6. The density of water and wastewater services: this may substantially increase the overall cost of construction of some of the newer technologies as excavations are required to reconnect each water service and by lateral pipes.

7. Water main material: The selection of the water or wastewater main material may have an impact on the rehabilitation or replacement technology. There are various water and wastewater main materials on the market for new pipe and rehabilitation technologies. Expansion and contraction (i.e. creep) is a factor that must be considered when selecting and designing the water or wastewater main.
8. The density of lateral connections: this can substantially increase the overall cost of construction of some of the newer technologies, if excavations are required to reconnect the water or sewer laterals.
9. Roadway conditions (traffic volumes, surface conditions, and remedial requirements): this may encourage or discourage the open cut method based on the economic analysis and construction related issues.

As the hydraulic and operational practices for water pipelines are different from wastewater pipelines, some rehabilitation techniques are preferred for certain categories over the other. More details about trenchless techniques can be found in the 2001 AWWA manual, Infraguide (2003) and Abbott (2005).

#### **2.4.2 Road Networks**

Generally speaking, road network mitigation actions can be classified into:

- Localized M&R: Applying a repair method to a small localized area of a pavement. Usually suitable when deterioration is only localized and typically has a minimal impact on extending the service life of the pavement.
- Globalized M&R: Application of a repair method to a large portion of the pavement section. This technique is more suitable when deterioration is more widespread and provides a small extension in pavement service life.

- Major M&R: Considered a full rehabilitation of the existing asphalt or base course. This technique provides a large extension in pavement service life and typically the most costly type of intervention.

## **2.5 Research Methods**

In the following subsections, a comprehensive literature review is offered to cover the research techniques utilized in the research methodology. The fuzzy set theory covers the basics of fuzzy set theory and offers a comprehensive literature review of fuzzy models used in the field of infrastructure management. Artificial neural networks in theory and methodology is covered and a comparison is presented to demonstrate the advantages and disadvantages of each technique. The fuzzy set theory and artificial neural network will lay out the basics for fuzzy neuro adaptive networks.

### **2.5.1 Fuzzy Set Theory**

To deal with vagueness of human thought, Zadeh (1965) first introduced fuzzy set theory which is based on the rationality of uncertainty due to impression or vagueness. A major contribution of fuzzy set theory is its capability of representing vague knowledge. A fuzzy set  $A$  is characterized by set of pairs  $\{x, \mu_A(x)\}$  where  $x$  is a member of a collection of objects, and  $\mu_A(x)$  is the grade of membership or membership function. Membership function represents the grade of possibility that an element  $x$  belongs to the set  $A$ . It follows that a membership function is a possibility function and not a probability function, which is usually defined subjectively (Buckley, 2005). Fuzzy set theory has the ability to realize a complex nonlinear input-output relation as a synthesis of multiple simple input-output relations (Zadeh, 1965).

The simple input-output relation is described in each rule. The boundary of the rule areas is not sharp but fuzzy. The system output from one rule area to the next rule area gradually changes. Another feature of fuzzy sets is the ability to separate logic and fuzziness (Yuan, 1995). Since conventional two-value logic-based systems cannot do this, their rules are modified when either logic or fuzziness should be changed (Zadeh, 1965). The fuzzy set modifies fuzzy rules when logic should be changed and modifies membership functions which define fuzziness when fuzziness should be changed. Fuzzy set theory was used by many researchers in the asset management to address certain concerns. Fares (2005) used hierarchical fuzzy expert system to rate the risk for water mains considering three factors (physical, environmental and operational). Salman (2010) proposed a fuzzy model to assess the risk consequences for wastewater collections based on physical, environmental, and operational factors by conducting interviews with experts and using elicited opinions to formulate knowledge base system. The knowledge base system is connected to ArcGIS to facilitate the visualization of the risk rating using the fuzzy expert system. Validation to the proposed system was conducted by experts interviews. Kleiner et al. (2005) proposed a fuzzy expert system to interpret distress indicators, observed during inspection and/or non-destructive evaluation (NDE) session, to obtain a condition rating of water transmission mains. This method considered both scarce field data and expert opinion. To build a fuzzy logic inference model five steps are needed (Ross, 2010):

1. Fuzzification of the inputs.
2. Applying fuzzy operators.
3. Applying implication method.

4. Aggregating all the output.
5. Defuzzification.

The theoretical background for each of the above mentioned steps is discussed comprehensively in Appendix A.

### **2.5.2 Artificial Neural Networks**

Artificial Neural Networks (ANN) are composed of simple elements called neurons operating in parallel and organized in layers inspired by biological nervous systems. In ANN, there is an input layer, a hidden layer and an output layer. The input layer is the model parameter to be considered in the analysis whereas the output layer represents the decision to be made. As in nature, the network function is determined largely by the connections between elements. The network training is performed to adjust the values of the connections (weights) between elements as shown in Figure 2-11. The aim of ANN training is that a particular input leads to a specific target output where the network is adjusted based on a comparison of the output and the target, until the network output matches the target. Hidden layers structures and numbers is determined using trial and error which is an acceptable practice used by many researchers (Hegzay & Ayed, 1998; Fahmy & Moselhi, 2009; Moselhi, Hegazy, & Fazio, 1991; Khan, Zayed, & Moselhi, 2010). The main advantage of ANN is the deployment of historical data for training the input neurons and modifying the neurons weights until they reach an output close enough to the original historical record of such output. The fundamental building block for neural networks is the single-input neuron, such as shown in Figure 2-11. There are three distinct functional operations that take place in this example neuron. First, the scalar input  $I$  is multiplied by the scalar weight

$w$  to form the product  $wI$ , again a scalar. Second, the weighted input  $wI$  is added to the scalar bias  $b$  to form the net input  $n$ . (In this case, you can view the bias as shifting the function  $f$  to the left by an amount  $X$ . The bias is much like a weight, except that it has a constant input of 1. Finally, the net input is passed through the transfer function  $f$ , which produces the scalar output  $O$ . The names given to these three processes are: the weight function, the net input function and the transfer function.

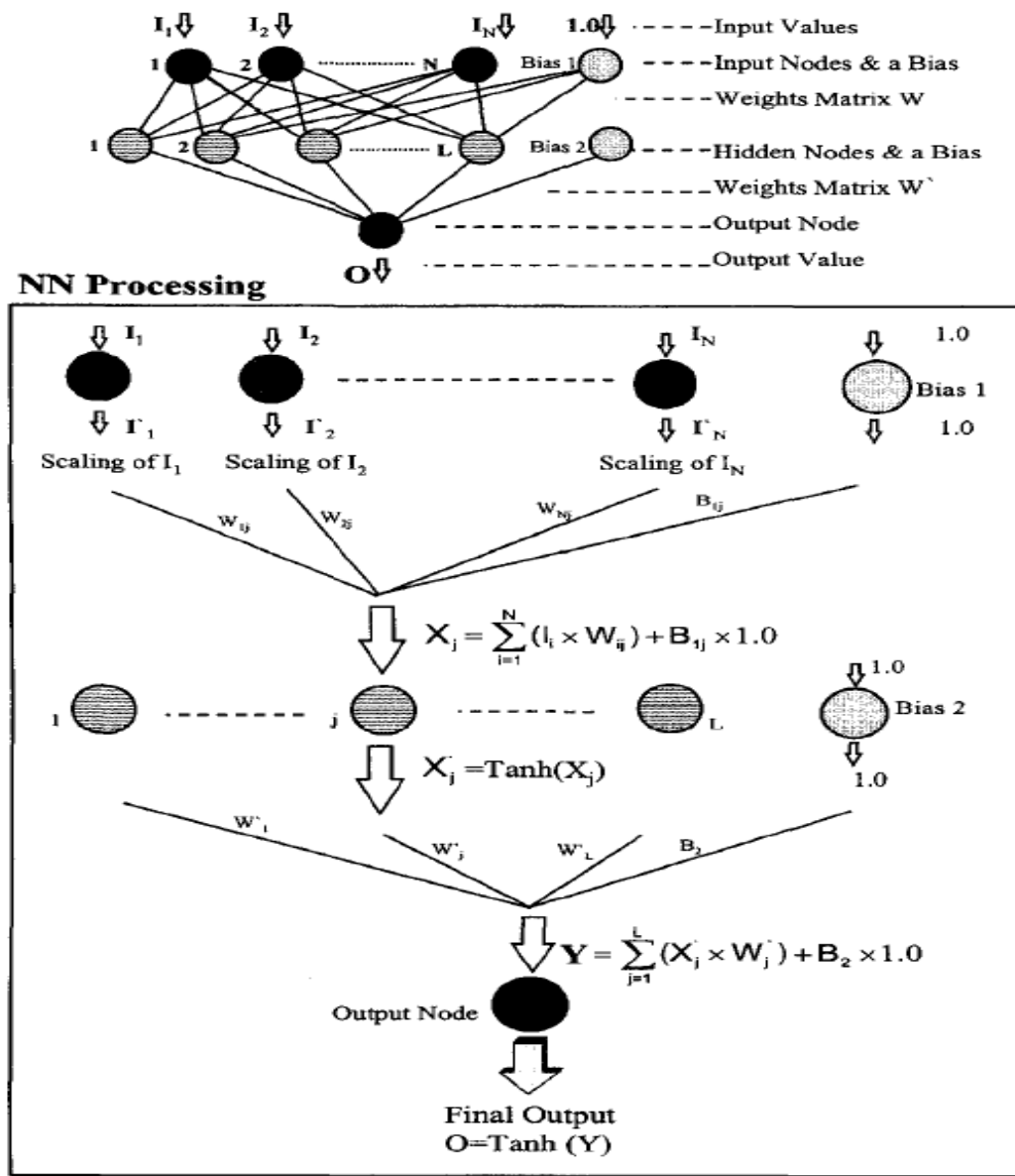


Figure 2-11 Schematic ANN (Hegazy and Ayed, 1998)



The weight ( $w$ ) and bias ( $b$ ) are both *adjustable* scalar parameters of the neuron. The central idea of neural networks is that such parameters can be adjusted so that the network exhibits some desired or interesting behavior (Achim, Ghotb, & McManus, 2007). Thus, the network training concerns particularly with adjusting the weight or bias parameters to map from inputs to output. Least Mean Square Error is used to measure the difference between the ANN output and original output by the following equation:

$$E = \sum_{n=1}^n (O - t)^2 \dots\dots\dots \text{Equation 2-7}$$

### 2.5.3 Optimization Models

Optimization problems may be defined as the couple ( $S, F$ ) where  $S$  is a set of feasible solution and  $F: S \rightarrow R$  is the objective function to be optimized for set for solutions in set  $S$ . A solution is said to be global optimal solution ( $s^*$ ) if it has a better value for objective functions than all other solutions in the search space ( $\forall s \in S, F(s^*) \geq F(s)$ ). Roughly, optimization models can be classified into exact and non-exact solution.

Exact solutions can be grouped into linear and non-linear programming models. Linear models are models with continuous decision variables that formulate with set of constrains the search space. In linear programming, the set of constrains and the objectives function are linear functions and there are many algorithms that can be used to find the optimal solutions for such problems (Hillier and Lieberman, 2004; Taha, 2008). Although this assumption essentially holds for numerous practical problems, it frequently does not hold and therefore, the non-linear programming is suitable for such cases (Hillier and Lieberman, 2004). Nonlinear programming includes many techniques to find the optimal solution based on the nature of the problem and whether the problem is constrained or not. Non-linear programming techniques include; the one-dimensional

search procedure, multivariable unconstrained optimization, the gradient search procedure, quadratic programming and non-convex programming. Each one of these non-linear programming techniques can be used in certain situations with certain limitations. Covering all the advantages and disadvantages of these techniques is out of scope for this research as it is covered comprehensively in many operations research text books (Hillier and Lieberman, 2004; Taha, 2008). However, the primarily common disadvantages of these types of techniques are: 1) they require large computational time when the search space increases 2) they possess significant mathematical complexity in problem formulation and procedures for algorithm solution for large spaces.

Infrastructure systems are considered as large scale systems that require near optimal solution that satisfies decision makers objectives in reasonable computational time. Hence, non-exact methods are appropriate when the objective is to find optimal solutions over large space of water, sewer and road assets. The search space in such case is considered complex because of the huge number of decisions variables available besides large number of alternatives that is available for each decision variable as will be shown in in Chapter 3. Genetic Algorithm is a suitable optimization technique over single populations' algorithms like tabu-search, local search procedure, simulated annealing for number of reasons. Genetic Algorithm allows for exploration of wide search space, operators to improve characteristics of the search space and provides the decision makers with a list of near optimal solutions in case of multi-objectives optimizations (Talbi, 2009).

## **2.6 Summary and Limitations in Current Research**

In this chapter, an extensive overview was provided to cover the current state of the art of interdependency and vulnerability assessment research and models. The interdependency classifications were reviewed comprehensively and subsequently interdependency models were classified into: spatial, functional and economical models. The interdependency models' foundation, inputs, processes, outputs and limitations were discussed. The vulnerability assessment basics and models were reviewed along with their required inputs, processes, outputs and limitations of each model. Following the vulnerability assessment, current state of art for water, sewer and road rehabilitation and replacement were presented as well. To conclude, the main limitations in the current state of art of asset management can be summarized as following:

- 1- Previous DSS for rehabilitation and maintenance policies were primarily implemented ignoring underlying spatial and functional interdependencies that exist between water, sewer and road networks.
- 2- For interdependency models, current models were oriented towards assessing functional and/or economic interdependencies between various interacted networks for disaster management (Santos & Haimes, 2004; Osorio et al., 2010; Karmakaret al., 2010; Roshani and Fillion, 2014). In asset management, decision makers maintain public capital intensive assets to meets customers' expectations not only to avoid catastrophic failures.
- 3- For vulnerability models, current state of the art focuses on studying independently factors affecting vulnerability due to spatial interdependency and

function interdependency (Roshani and Fillion, 2014; Mandapaka et al., 2012; Wei et al, 2009).

4- For interdependency and vulnerability models:

- i. Previous studies fail to objectively allocate the diminished resources for intervention policies on network levels (Ezell, 2005; Ouyang et al., 2009; Osorio et al., 2010).
- ii. Previous studies did not consider operation and maintenance reports of civil infrastructure networks in understanding causes for increasing or decreasing vulnerability of interdependent assets.
- iii. Previous studies considered primarily hypothetical examples or small size networks and did not test the stability and suitability to real large scale networks.

# Chapter 3 : DATA COLLECTION

## 3.1 Introduction

In this chapter, two datasets were analyzed not only to understand current practices of asset management but also to structure and develop the proposed framework and its models. Two datasets were obtained from the Cities of London and Hamilton in Ontario, Canada. Each dataset was analyzed using the statistical toolbox of MATLAB 2013. The objective was to; 1) understand what data attributes were utilized in each city, 2) analyze each city practices in configuring and storing collected data, 3) determine which factors are influencing vulnerability assessment of water, sewer and road assets based on operation and maintenance reports, 4) summarize common observations found among the two case studies and 5) if possible, discuss the list of selected factors for vulnerability assessment with common observations with cities officials. Figure 3-1 shows an overview of the sections covered in this chapter.

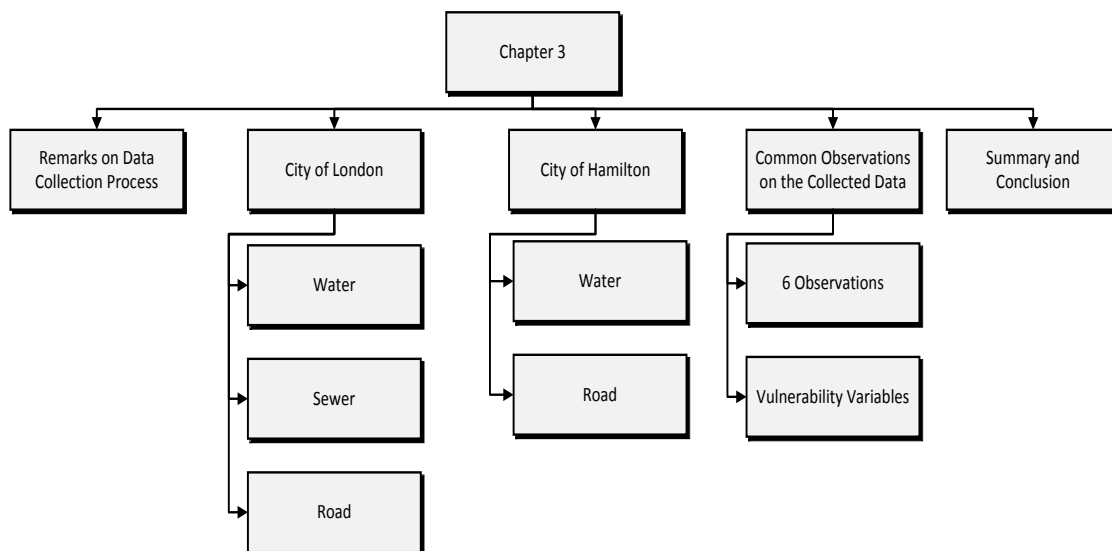


Figure 3-1 Chapter 3 overview

### **3.2 Remarks on Data Collection Process**

The following should be noted on the data collection process:

1. The state of infrastructure (SOI) reports for both cities were utilized to gain insights into the current state of water, sewer and road infrastructure networks. The 2013 SOI report was available for the City of London. The 2005 and 2009 SOI reports were available for the City of Hamilton but its dataset was updated till 2005.
2. For City of Hamilton:
  - a. Only datasets for water network and road network were available. The water network dataset had 6 attributes and the road network dataset had 5 attributes.
  - b. The operation and maintenance reports were available for water assets only.
3. For City of London:
  - a. Datasets for water, sewer and road assets were available. The water and sewer network dataset had 11 attributes and the road network dataset had 6 attributes.
  - b. The operation and maintenance reports were available for water and sewer assets.

### **3.3 City of London**

The city of London according to the 2013 SOI report owns; 1) water network of 1,570 km with total replacement value of \$2.7 billion, 2) sewer network of 1,430 km

with replacement value of 2 billion, 3) road network of 3,717 km with replacement cost of 1.8 billion. The collected datasets consists of 9145 datasets for road network, 44973 for sewer network and 24567 for water network as shown in Figures (3-2, 3-3, 3-4).



Figure 3-2 Water network, London, Ontario



Figure 3-3 Sewer network, London, Ontario





Figure 3-4 Road network, London, Ontario

Only 1895 road datasets, 10500 sewer datasets and 2500 water datasets were used after removing incomplete records. The condition of the three assets was measured on 5 points scale (very poor, poor, fair, good and very good) as shown in Figure 3-5. By examining closely Figure 3-5, the majority of water, sewer and road assets were found to be below fair. Summary of some statistical measurements for water, sewer and road network of are shown in Tables (3-1 to 3-4).

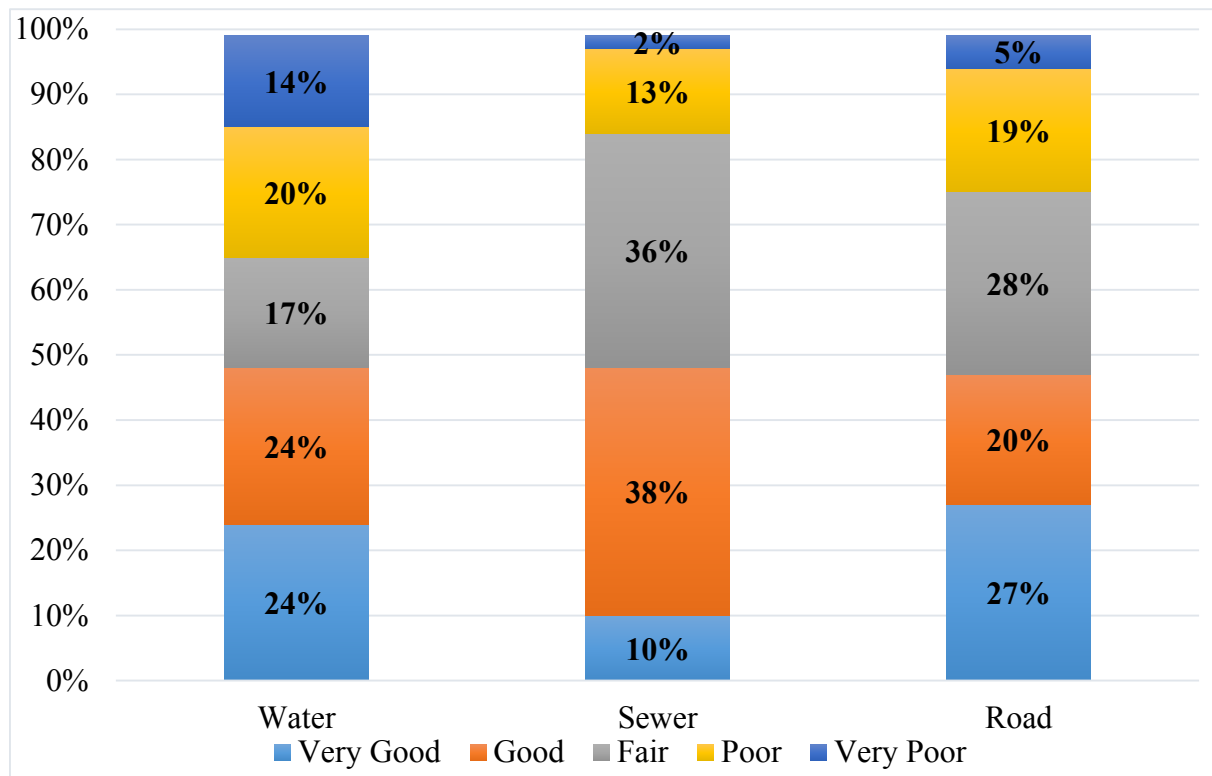


Figure 3-5 Condition ratings for water, sewer and road assets (SOI, 2013).

Table 3-1 Quantitative data attributes for water network, City of London

Attribute	Mean	Min	Max	Sdv
Age (years)	62.02	28	137	17.44
Breakage rate (breaks/year/m)	0.012	$5.4 \times 10^{-5}$	0.59	0.02
Depth (ft)	5.88	0.5	1.5	1.08
Length (m)	211.41	2.1	840	145.72
Pipe Diameter (mm)	163.44	50	900	51.06
Remaining useful life (years)	87.97	13	122	174.4

Table 3-2 Qualitative data attributes for water network, City of London

Attribute	Values	percentages
Pipe Material	Cast Iron	93.83
	CPP	0.16
	Ductile Iron	5.55
	Galvanized Pipe	0.08
	PVC	0.19
	Steel Pipe	0.19
Soil Type	Sand	25.36
	Gravel	7.87
	Stone	2.00
	Rock	1.00
	Clay	60.43
	Loam	1.00
	Backfill Material	2.34

Table 3-3 Quantitative data attributes for sewer dataset, City of London

Attribute	Mean	Min	Max	Sdv
Length (m)	62.1269	0.22743	2237.14	46.27263
Age (years)	70.1	12	110	35.1
Depth (ft)	2.617896	0	15.6	1.660014
Diameter (mm)	455.8864	150	7000	362.142

Table 3-4 Qualitative data attributes for road dataset, City of London

Attribute	Values	percentages
Road Type	Paved	98.80
	Gravel	0.45
	Tar and Gravel	0.45
	Concrete	0.31
Traffic Type	Heavy	14.25
	Medium	29.67
	Light	56.08

Operation and maintenance reports for water assets and sewer assets were analysed. These operation and maintenance reports include the following data:

- 1- Asset condition.
- 2- Construction date.

- 3- Replacement date.
- 4- Road condition.
- 5- Description of breakage; rotten, blowout, corrosion cracked around .....etc.
- 6- Causes of breakage; contractor, corrosion, pressure...etc.
- 7- Damages due to breakage; road surface, shoulder of the road, road cut .....etc.

When analyzing operation and maintenance reports for the water network, it was found that most of failure records were due to corrosion, settlement, deterioration of pipe condition and improper bedding as shown in Figure 3-6. The majority of these failures were for pipes with diameter less than 200mm and length less than 400m. Most failures were encountered in clay soil, 60.4%, and sand soil, 25.5%. Cast iron pipes occupied around 93.3% of failure records in City of London data. Based on the 2013 SOI report, water and sewer pipes installed in the 1930's through the 1970's are experiencing very high rate of failure.

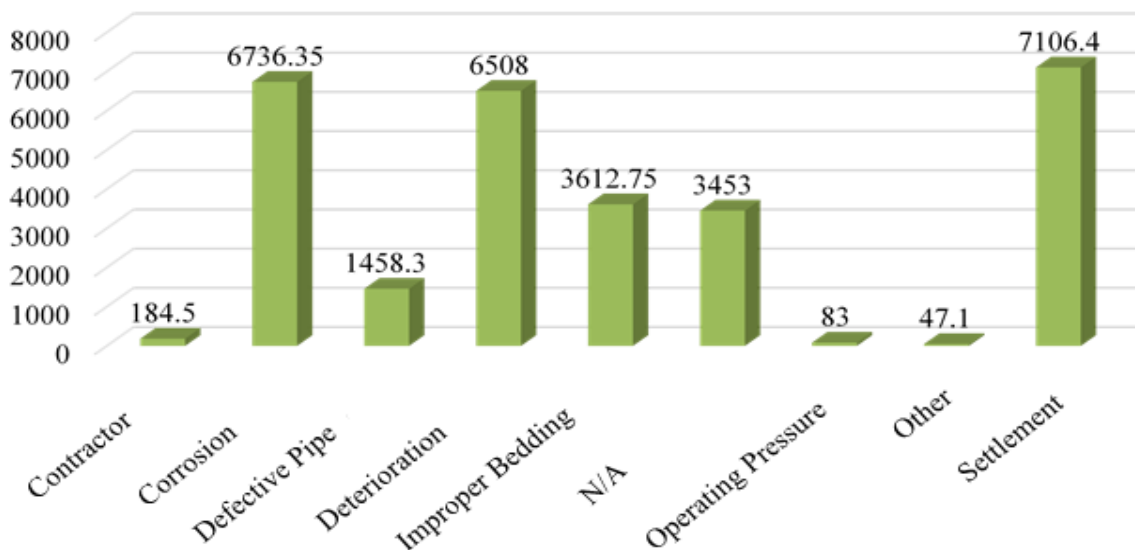


Figure 3-6 Failure causes for water mains

The design of the water database is shown in Figure 3-7. Each water asset, feature class, is designed to have its physical and functional attributes stored in a separate table. The table is located inside the ArcGIS geodatabase and it is called feature attribute table. Any feature class can have only one geographic location and therefore each feature attribute table is connected to one geographic table and such relationship is said to be one to one (1 to 1) as shown in Figure 3-7. The same design is maintained for the operation and maintenance reports as each asset has only one corresponding report (1 to 1). The sewer network database had the same water database configuration shown in Figure 3-7. The configuration of the road network database is shown in Figure 3-8. The road database has also similar configuration to the sewer and water databases. The only difference is that road assets in City of London were not attached to operation and maintenance reports like the water and sewer assets.

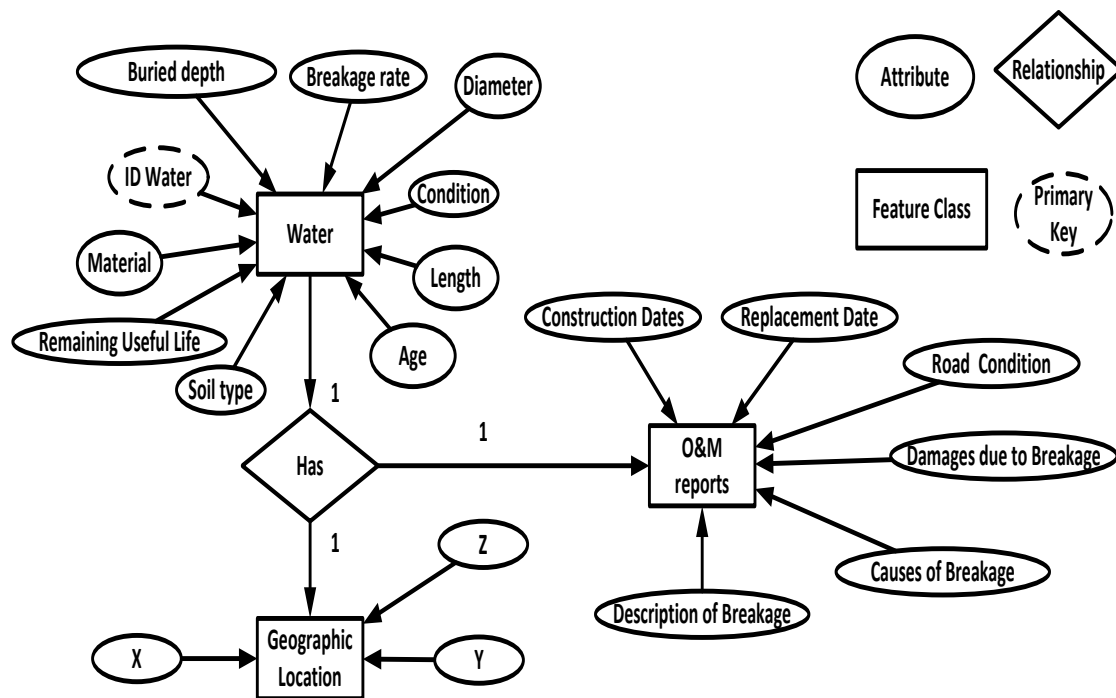


Figure 3-7 Water database configuration, London

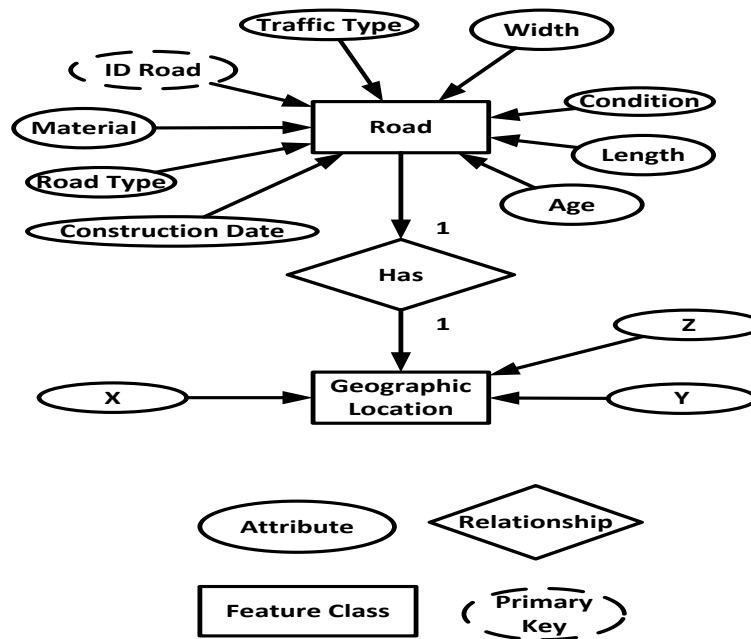


Figure 3-8 Road database configuration, London

### 3.4 City of Hamilton

The collected data presented in this section is for the City of Hamilton water distribution and road network as shown in Figure 3-9. City of Hamilton owns 1950 km of water assets with replacement value of CAD 1.82 billion and 3000 km of road assets with replacement value of CAD 3.25 billion (SOI Report, 2005). The collected datasets consists of 37,502 datasets for sewer network, 43,031 for water network and 12,350 for road network. After removing incomplete records, 7,502 datasets for sewer network, 10,031 for water network and 6,000 for road network were considered for the statistical analysis. Summary of some statistical observations for water assets are shown in Table 3-5 and Table 3-6.

Table 3-5 Quantitative data attributes for water datasets, City of Hamilton

Attribute	Mean	Min	Max	Sdv
Age (years)	59.73	8	113	21.08
Buried Depth (m)	1.56	0	2.1	0.17
Flow pressure(psi)	31.61	0	95	24.36
Length (m)	62.15	0.3	472	75.13

Table 3-6 Qualitative data attributes for water datasets, City of Hamilton

Attribute	Values	Percentages
Pipe Material	Cast Iron	88
	Ductile Iron	5
	High Density Polyethylene (HDPE)	5
	Polyvinyl Chloride (PVC)	2
Soil Type	Sand	83.7
	Silt	0.01
	Gravel	4
	Clay	12
	Loam	0.01
	Peat	0.01

The asset condition of water network and road network is measured on scale of 1 to 5 where 1 is excellent condition and 5 is failure condition. Operation and maintenance reports for water assets and sewer assets were analysed. These operation and maintenance reports include the following data:

- 1- Asset condition.
- 2- Construction date.
- 3- Replacement date.
- 4- Road condition.

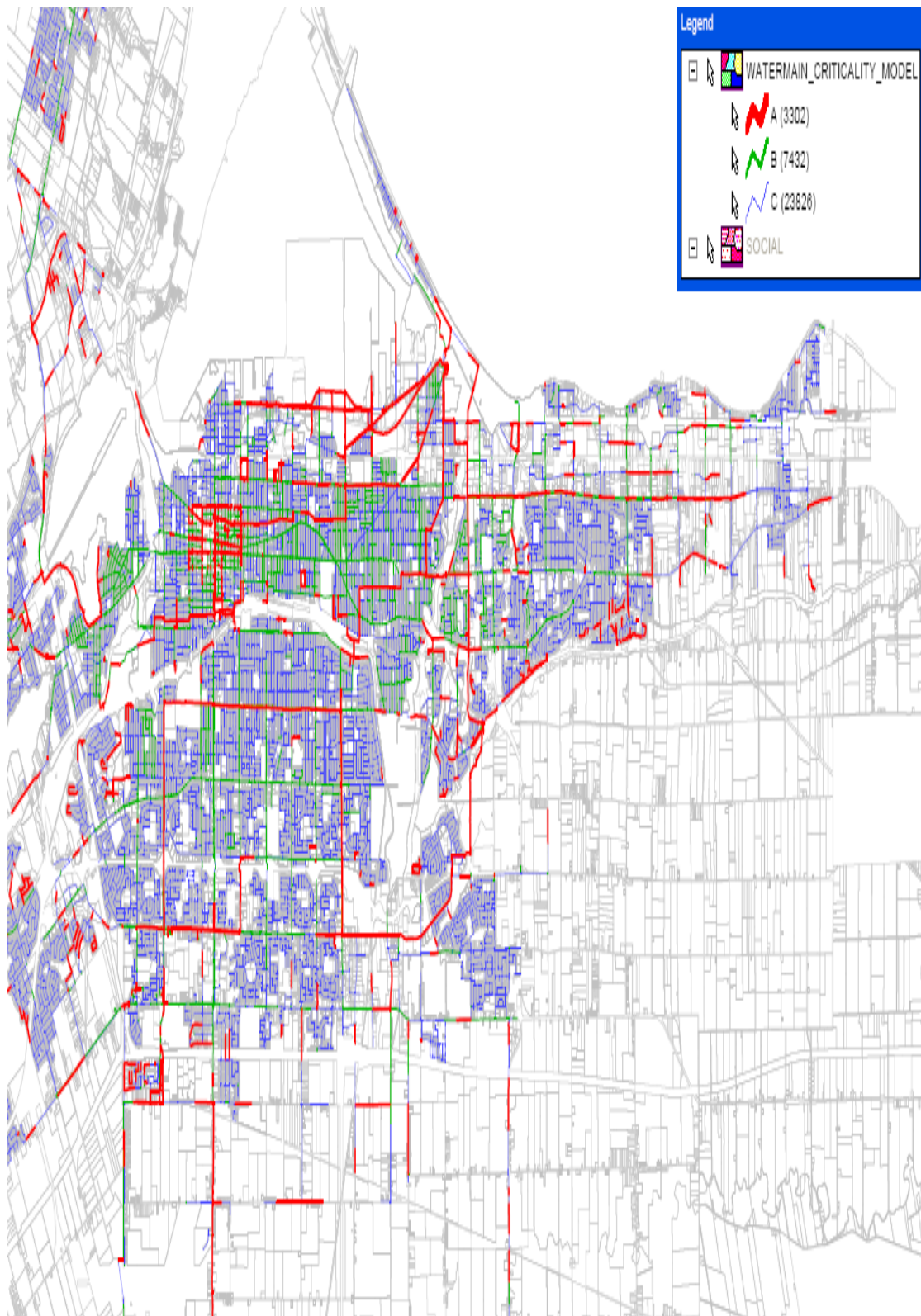


Figure 3-9 Water and road network, City of Hamilton, Ontario





### **3.5 Common Observations on the Collected Data**

Based on the statistical analysis of operation and maintenance reports and discussion with three of cities officials, the following observations were found common in the two datasets:

Observation 1: Most of water and sewer failures were attributed to pipe material, soil conditions, uneven manufacturing quality, installation practices, and traffic loading.

- a) Most failure records, approximately 85%, were for pipes with small and mid-size diameter.
- b) Most failure records, 60% for London and 80% for Hamilton, were for cast iron pipes.
- c) Pipe segments less than 200 m in length were found to be prone to failures.
- d) Pipe failures were encountered frequently in clay soil and sand soil (6 soil types for City of Hamilton- 7 soil types for City of London).

Observation 2: Close to 20% of the failures encountered in road assets were attributed to deteriorated water or sewer assets.

Observation 3: Response time to disruptions due to structural or functional failures of water, sewer and road assets is a critical indicator for city officials and policy makers. Based on infraguide best practices and operation guidelines, the response time should be less than 4 hours (SOI, 2005).

Observation 4: City officials are sensitive to the type of customer who will be affected by any disruption. They are less keen to encounter failures in any of the three

assets for commercial and/or industrial customers due to high economic costs and consequences.

Observation 5: Most of the reported failures in road networks were reported for local, collector and arterial roads with less failures reported for freeway, expressway and sidewalks (SOI, 2013).

Observation 6: The two datasets had similar practices in storing their collected data for asset management. Physical and functional factors were stored in one separate table and the same was true for operation and maintenance reports if available. This will facilitate the development of the proposed models in Chapter 4 as no special modifications are needed in implementing such models for each city.

Such observations suggest:

- Vulnerability of water and sewer assets is a function of spatial factors; pipe condition, neighboring asset condition, soil condition, pipe length, buried depth and pipe diameter and functional factors; number of affected customers, customers' type and response time.
- Vulnerability of road assets is function of spatial factors; road condition, neighboring asset condition, soil condition, pipe length, neighboring pipe buried depth, pipe diameter and functional factors; average daily traffic, road type and response time.

The betweenness centrality will be added later to the functional factors and the justification for this will be explained in next chapter.

### **3.6 Summary and Conclusion**

Two datasets from Cities of London and Hamilton were analyzed along with operation and maintenance reports. By analysing the configuration of the two datasets, it was found that the two cities had similar practices for data structure and storage where physical and functional factors were stored in one table separated from operation and maintenance reports. Operation and maintenance reports were used to determine which factors are influencing the vulnerability of water, sewer and road assets. Common observations found among the two case studies were summarized as well. Based on the literature and by examining operation and maintenance reports, 10 factors were identified for assessing vulnerability of water, sewer and road assets; 6 for spatial and 4 for functional. In the next chapter, three computational models will be developed to assess vulnerability of water, sewer and road assets based on the identified 10 factors.

# **Chapter 4 : DEVELOPED RESEARCH FRAMEWORK**

## **4.1 Introduction**

This chapter describes three models developed for optimizing intervention policies for likely vulnerable civil infrastructure networks considering their spatial and functional interdependencies. The first model is the interdependency model which consists of two modules; spatial module and functional module. The first identifies which assets are spatially interdependent using ArcGIS geoprocessing tools. The second identifies asset's degree of connectivity with its neighbouring assets using betweenness centrality. The developed functional module will aid in recognizing the likely influence of an asset failure on its neighbouring assets' performance. The output of the assessment model is in the form of bundles of spatially and functionally interdependent assets.

For vulnerability assessment, three computational models are developed to rate vulnerability of civil infrastructure systems considering their spatial and functional interdependencies with neighboring assets. These models are; 1) multi-attribute utility theory (MAUT), 2) artificial neural network (ANN) and 3) fuzzy c-mean clustering (FCM). For the MAUT model and based on the identified factors from operation and maintenance reports, surveys were sent to 65 experts and their feedback was elicited to construct utility functions to rate the degree of vulnerability of interdependent assets. The response rate of the survey was 75%. On the other hand, the developed ANN model utilizes self-organized mapping algorithm (SOM) to rate vulnerability of these assets

based on recognized patterns in each dataset. The developed ANN model is utilized because it can rate vulnerability of interdependent assets based on observed patterns in each dataset and hence less involvement is required from experts. The third computational model is FCM which is capable of accounting for ambiguity associated with experts' judgement in rating vulnerability of interdependent assets. In the FCM model, each dataset can belong to more than one rating, and each element of the dataset is associated with a set of membership grades. The FCM model is an iterative process for assigning these membership grades and then using them to assign data elements to one or more vulnerability ratings.

Finally, the SD model is developed to help identify possible least cost intervention policies for interdependent infrastructure assets that meet customers' expectations and decrease assets' vulnerability. The developed SD consists of 23 variables and 8 causal feedback loops which were extracted and constructed based on literature review and four unstructured interviews with experts in the domain of municipal asset management from Cities of London and Hamilton, Ontario. At the bundle level, the SD model is supplemented with dynamic programming algorithm for finding and ranking the available intervention policies. At the network level, the SD is supplemented with a genetic algorithm to find a near optimal policy considering the ranked policies identified by the dynamic programming algorithm. The single objective genetic algorithm (SOGA) is modified by; 1) integrating a query based filtering function into the SOGA to cluster similar bundles, 2) adding dynamic memory to store worst solutions to prevent the regeneration of such solutions in next iterations and 3)

modifying the behavior of the mutation function to improve the convergence rate of the genetic algorithm. Summary of the topics covered in this chapter is shown in Figure 4-1.

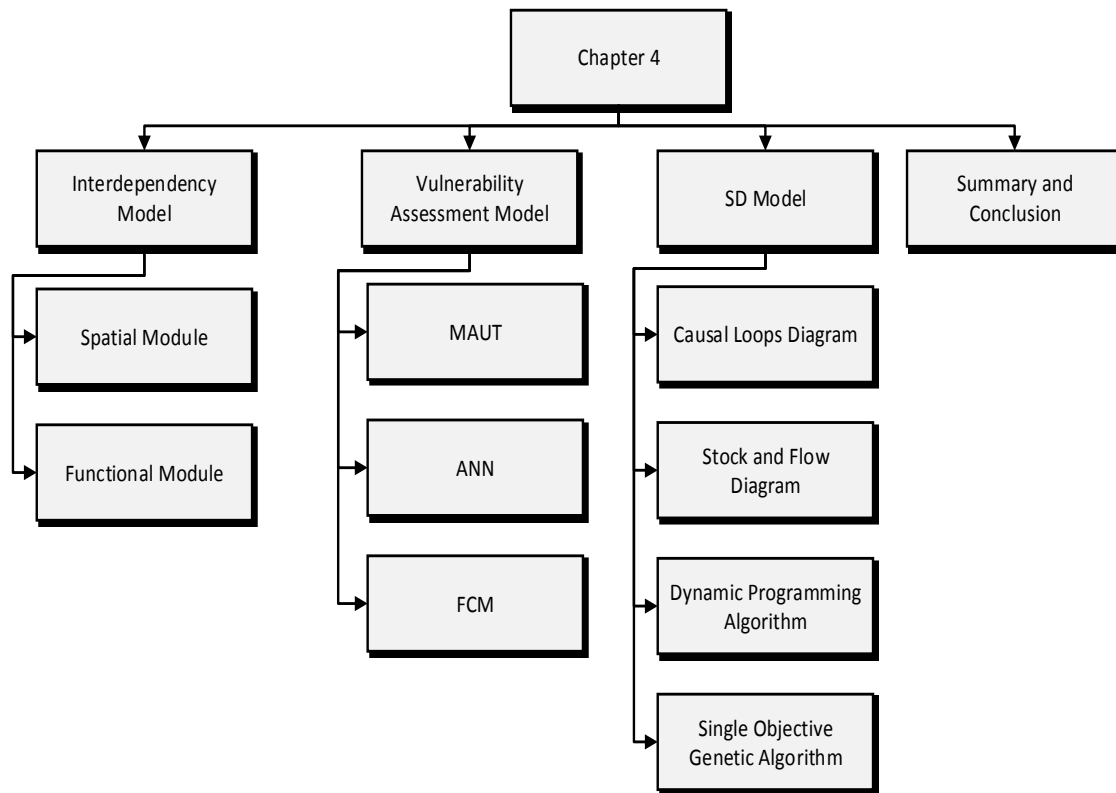


Figure 4-1 Chapter 4 overview

## 4.2 Interdependency Assessment Model

This model consists of: 1) spatial module, and 2 functional module. The following subsections describes the development made in each module. The spatial module is developed to construct bundles of spatially interdependent assets by utilizing ArcGIS geoprocessing tools. The second identify asset's connectivity with its network and hence understand to what extent it can compromise the performance of their respective networks. The functional module is utilizing betweenness centrality to determine asset's connectivity with its network.

#### **4.2.1 Spatial Module**

The spatial interdependency model is developed to encapsulate assets that are spatially interdependent, co-located in the XYZ planes, using ArcGIS geoprocessing toolbox. ArcGIS is a geographic information system for visualization, analysis and reporting of spatial information using a set of toolboxes called geoprocessing. Geoprocessing is a methodical execution of a sequence of operations on geographic data to create new information using automated spatial analysis. For infrastructure networks, the assets are represented by a feature class where each feature has a geometric profile, which inherits its attributes from the main object. For example, the water network is represented by connected lines with their geographical location. Also, each water asset has attributes such as condition, age, material and diameter...etc. These attributes are inherited from the main water object and are adjusted to reflect the characteristics of each individual water asset and such attributes are stored in a geographic database for further visualization, analysis and reporting inside ArcGIS.

The geoprocessing toolbox is utilized to take two different datasets (i.e. water and road) and find a new single dataset with neighboring assets and their corresponding attributes. The spatial module starts by attribute selection queries to select the targeted zones of water, sewer and road assets. By using attribute selection queries, the decision maker can choose between:

- 1) Performing the spatial analysis on specific zones from the targeted networks.

For example, the decision maker could be interested only in finding bundles of interdependent assets in a neighborhood or a suburb or a subnetworks to optimize intervention policies for such zone only.



- 2) Performing the spatial analysis on assets with specific attributes from the targeted networks. For example, the decision maker could be interested in rating vulnerability for water pipes with a diameter less 150mm.
- 3) Performing the spatial analysis on the entire network.

After the attribute selection queries, a buffer is generated around the study zone. A buffer is dynamic or static geometric boundary around the selected feature and it encapsulates the study zone. If there is another feature falling within that boundary, it will be interdependent with that feature. The width of buffers is designed to vary dynamically to account for the asset width (i.e. road width, water or sewer diameter) or to be static; based on the decision maker's preferences. The length of buffers can be assigned based on length of assets segment (i.e. from one valve to another, from one manhole to another, from one intersection to another) or the decision maker's preferences. Subsequently, a selection query using location attributes is utilized to select the intersected layers of water, sewer and roads. Next, the union module of the geoprocessing toolbox is deployed to build four new layers of spatially interdependent assets (water and sewers, roads and sewers, roads and water and road, sewer and water assets). The developed spatial interdependency algorithm is shown in Figure 4-2. The output is new layers with new datasets that contain characteristics of intersected assets as shown in Figure 4-3.

In Figure 4-3, the entity relationship for the spatial module is shown for interdependent water and road assets. The water feature class is designed to have 14 attributes and the road feature class is designed to have 13 attributes.

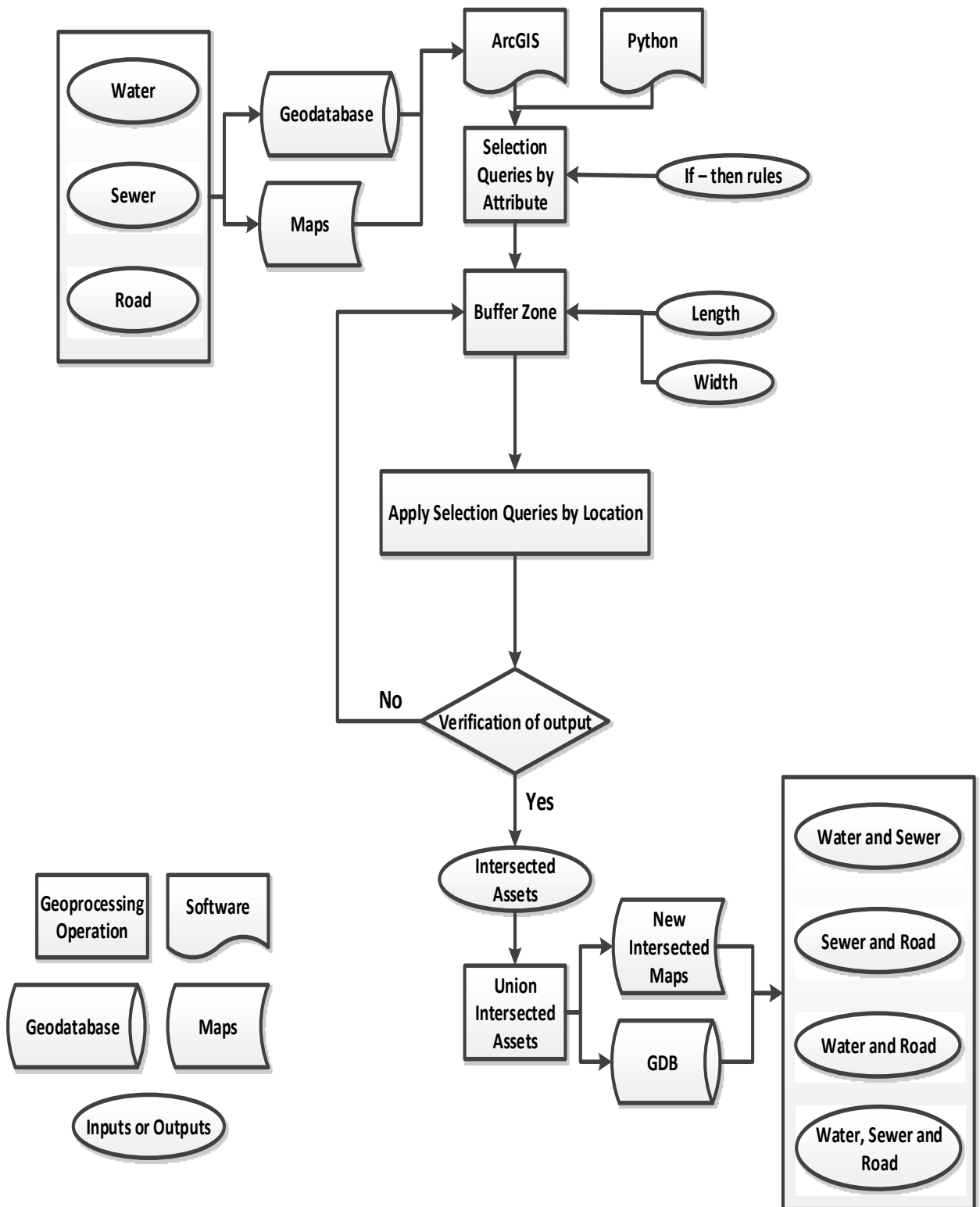


Figure 4-2 Spatial interdependency model

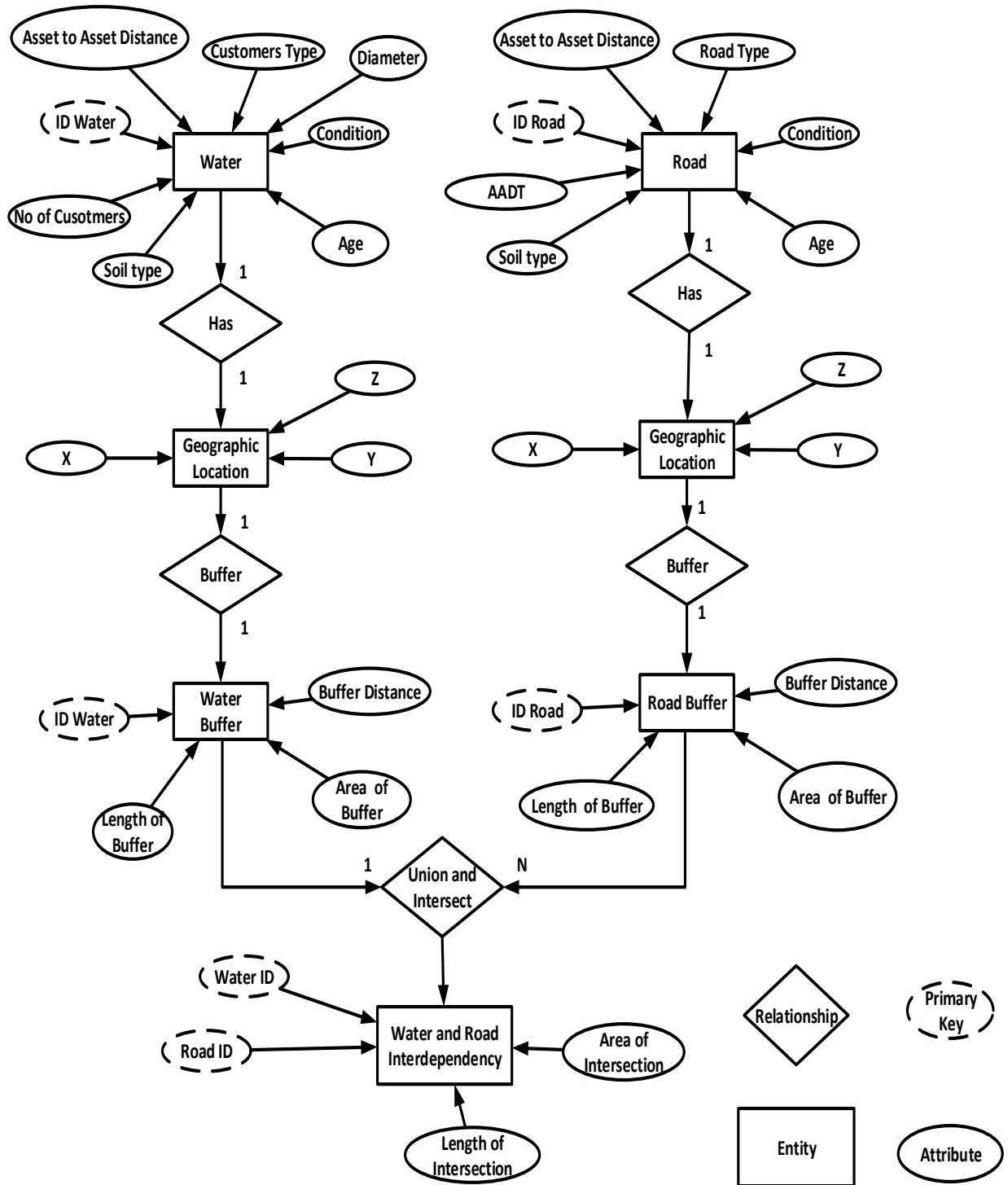


Figure 4-3 The developed entity relationship diagram for the spatial module (water and road)

These attributes are stored in a table inside the geodatabase called feature attribute table. There are seven entities with five relationships as shown in Figure 4-3. For example, any feature class (asset) can have only one geographic location and therefore each feature attribute table is connected to one geographic table and such relationship is said to be one to one (1 to 1) as shown in Figure 4-3. The same design is maintained for the buffer table as each asset has only one corresponding buffer (1 to 1). However, any feature class (asset) can intersect with more than one feature class, therefore the relationship between any two feature attribute tables is designed to be one to many (1 to N). In the entity relationship diagram, any two tables are related through one primary key which is the asset ID as shown in Figure 4-3.

Using the geoprocessing operation shown in Figure 4-2, a number of new fields are added to the geodatabase in a separate table called interdependent assets table. In that table, new fields are added to represent the characteristics of spatially interdependent assets. For example in case roads and sewers are intersected, the soil type between them, the distance between these two assets are housed in these new fields. The data housed in these new fields is used as input for the vulnerability model to assess the extent of any asset failure on the performance of spatially interdependent assets.

#### **4.2.2 Functional Interdependency model**

After determining the spatial interdependent group of assets, the decision maker needs to understand how well each asset is connected to its network and hence judge its expected contribution in reducing the nearby assets functionality in case of unforeseen events or as a consequence of planned interventions. To do so, graph theory principles are used to understand the connectivity of each asset through a number of metrics.

Accordingly, networks are represented throughout vertices and edges  $G(V, E)$  and the flow between any two vertices is represented by the edges.

Consider for instance Figure 4-4-a, it depicts a small road network with seven vertices (road assets) and eight edges between them to represent the average daily traffic flow. The failure effects for a vertex that is connected with large number of vertices are likely higher than that of a vertex connected with a small number of vertices. Hence, the degree of vertex can measure the number entering or exiting edges, connected vertexes, normalized using Equation 4-1.

$$\text{Norm-deg}(V_i) = \frac{\sum E_{in} + \sum E_{out}}{N-1} \dots\dots\dots \text{Equation 4-1}$$

Where  $\text{deg}(V_i)$  is the degree of a vertex,  $E_{in}$  number of entering edges and  $E_{out}$  is number of exiting edges.

In asset management context, decision makers are interested in capturing which assets can significantly damage the network performance more by their structural or functional failure. In Figure 4-4-a, two nodes C and D have different scores for degree of vertex, 2 and 3 respectively. Based on such metric, C is more important than D as any failure in node C will affect three other roads but D will affect two roads only. To show the inconsistency in considering such a metric, the shortest path between any two vertexes needs to be introduced. The shortest path between nodes i and j ( $g_{ij}$ ) is a path allowing users to travel from node i to j using the minimum number of edges. Based on the shortest path, users cannot travel from one side to the other side of the network without using node D 9 times and node C 8 times.

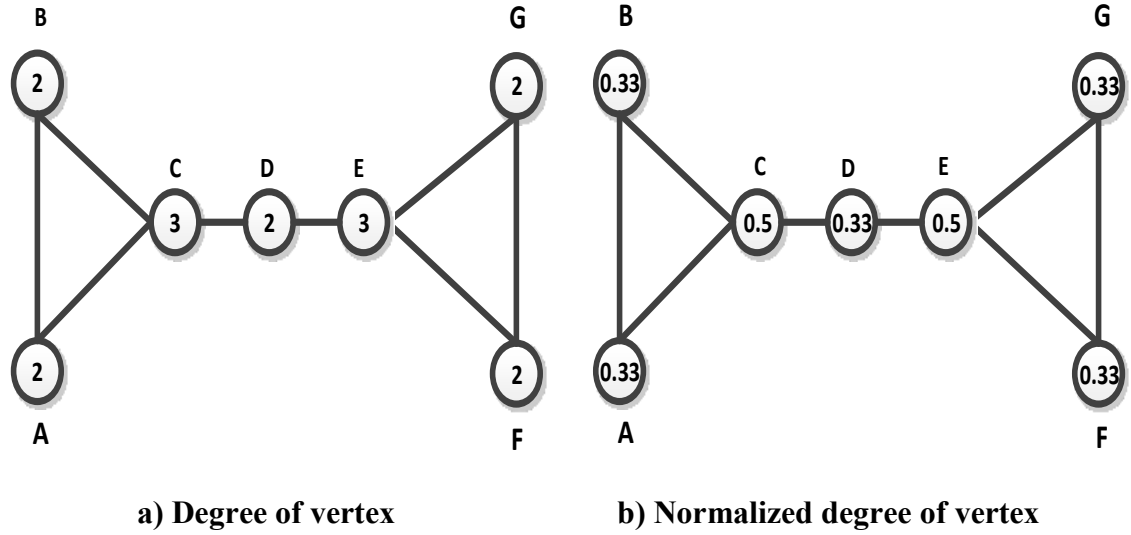


Figure 4-4 Normalized and non-normalized degree of a vertex

Betweenness centrality reflects which vertices are the most influential in the network and hence it reflects which ones control the flow in the network. Betweenness centrality accounts for how many pairs of vertices (i,j) will have vertex k as a node on their shortest path. Hence, the betweenness centrality for a vertex can be determined by the following equation:

$$\text{bet}(k) = \frac{\sum_{i < j} g_{ij}(k)}{g_{ij}} \dots\dots\dots \text{Equation 4-2}$$

Where  $g_{ij}(k)$  is number of shortest paths between  $ij$  with vertex  $k$ ,  $g_{ij}$  is the number of shortest paths between  $i$  and  $j$ .

The normalized score for betweenness centrality can be determined by the following equation:

$$\text{Norm-bet}(k) = \frac{\text{bet}(k)}{N(N-1)(N-2)} \dots\dots\dots \text{Equation 4-3}$$

Where  $N$  is the number of vertexes in the network

In this normalized score, the betweenness centrality is normalized by the number of possible pairs between node  $k$  and all network nodes. This normalized score was presented for studying social or information networks where it is possible for a vertex to be connected to every other vertex in the network (Newman, 2003). In asset management context, it is not rational to make such assumption and therefore the normalized betweenness centrality is modified to be the relative ratio between the betweenness centrality of vertex  $k$  and the maximum betweenness centrality score.

$$RBC(k) = \frac{bet(k)}{\max(bet)} \dots\dots\dots \text{Equation 4-4}$$

Where  $\max(bet)$  is the maximum betweenness score in the network

The relative betweenness centrality will reflect the vertex relative importance compared to the most influential vertex in the network and hence understand its likely effect on the network's functionality. Figure 4-5 shows the developed functional module algorithm. In this algorithm, the decision maker starts by importing the geometric layout of the network from ArcGIS format (mxd) to a format called, GML, geography markup language format as shown in Figure 4-5.

The geography markup language format (GML) is the XML grammar defined by the open geospatial consortium (OGC) to express geographical features. The GML files of GIS maps serves as a modeling language for geographic systems as well as an open interchange format for geographic maps; vector maps or raster maps. After converting the geometric layout from mxd format to GML format, the algorithm starts by building up the edges and vertices lists needed for calculating the betweenness

centrality. After calculating the betweenness centrality for targeted assets, results can be exported into the ArcGIS geodatabase or to a new excel sheet.

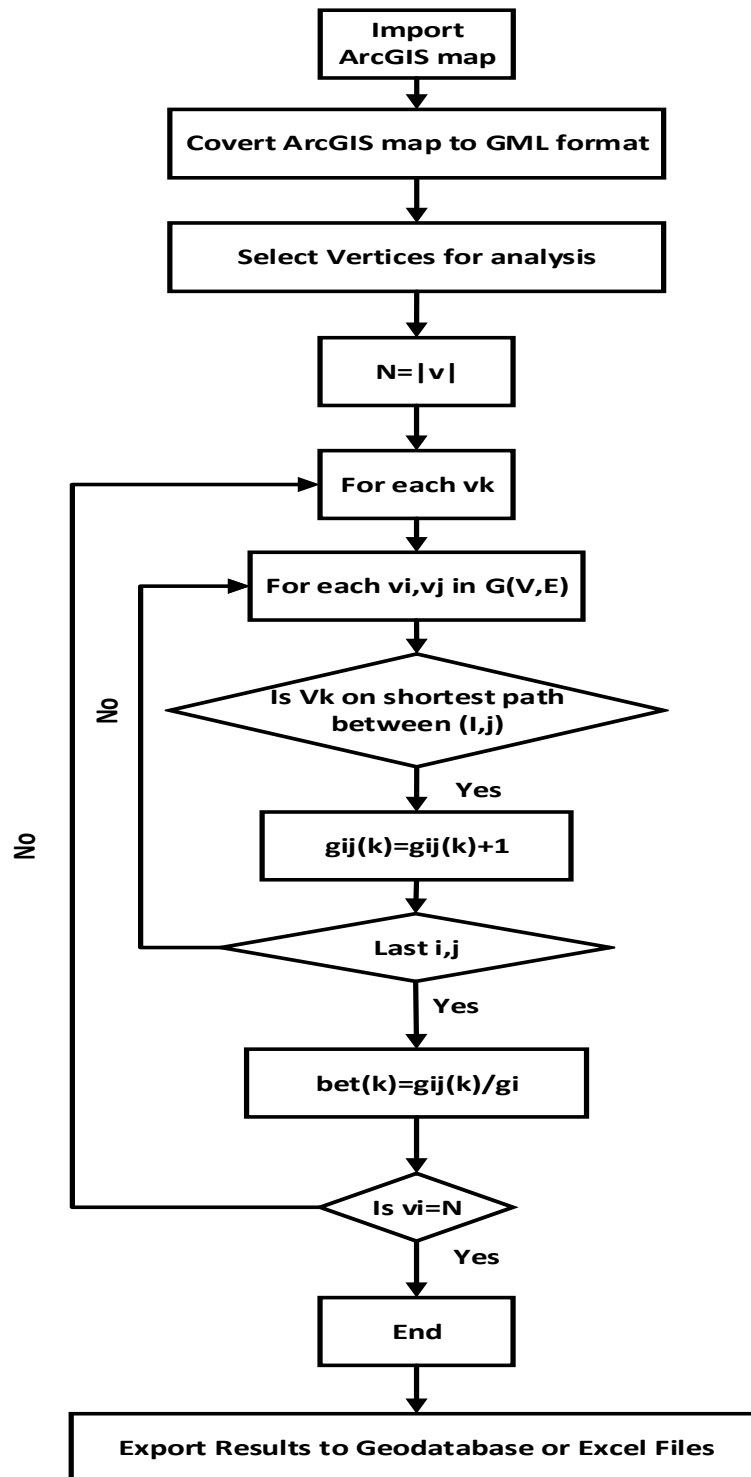


Figure 4-5 The developed functional module algorithm



### 4.3 Vulnerability Models

As mentioned before, Vulnerability is defined in this research as the degree of susceptibility to structural or functional failures as a result of being interdependent with neighboring assets. Hence, there are two types of vulnerabilities: 1) spatial vulnerability and 2) functional vulnerability. Based on the literature and by examining operation and maintenance reports, 10 factors were identified for assessing vulnerability of water sewer and road assets; 6 for spatial and 4 for functional. An overview of the vulnerability model is shown in Figure 4-6. Three computational techniques are developed for modeling vulnerability among interdependent assets:

- 1) MAUT: This model relies extensively on experts' judgment in assessing vulnerability of interdependent assets. Experts are asked to assign relative weights for each factor of the ten identified factors. For each asset type, experts are subsequently asked to establish utility functions for vulnerability rating. For example, experts are asked to establish the utility functions to rate vulnerability of a road asset given that the interdependent asset is water and repeat the same procedures if the interdependent asset is sewer.
- 2) ANN: Unlike the MAUT model, the ANN model doesn't require extensive feedback from experts with various backgrounds to establish a vulnerability assessment model. Instead, this technique utilizes recognized patterns in each dataset to assess vulnerability of interdependent assets. The ANN model utilizes a self-organizing map algorithm (SOM) to produce a two-dimensional discretized representation of the input space called a map. In this map, each asset is clustered (rated) based on the ten identified factors.

- 3) FCM: This model is similar to the ANN model as it utilizes recognized patterns in each dataset to establish membership functions for each of the identified factors. The FCM model is capable of accounting for ambiguity associated with experts' judgement in rating vulnerability of interdependent assets.

The following subsections illustrate the three developed computational techniques and how each model is assessing vulnerability of interdependent assets using the identified factors from Chapter 3.

#### **4.3.1 MAUT**

This model utilizes experts' judgment to construct utility functions for rating vulnerability of interdependent assets. The MAUT is well documented in the literature (Torrance et al, 1985; Moselhi and Martinalli, 1994; Ishizaka and Nemery 2013). The relative weight for each factor is assigned using expert's judgment. Surveys were sent to experts in the domain of municipal asset management of water, sewer and road networks.

The number of surveys was 65 with a response rate of 75%. The responses were elicited from asset officials (10%), operators (30%) and consultants (60%) within USA and Canada. The experts' judgment was elicited and used to construct utility functions for rating vulnerability of interdependent assets inside Excel environment and automated using VBA. In these surveys, experts were asked to; 1) assign relative weights for the spatial and functional vulnerability factors for water, sewer and road assets, 2) construct utility functions for each factor. Figure 4-7 and Figure 4-8 show the elicited weights for spatial and functional factors to rate vulnerability of water and sewer assets

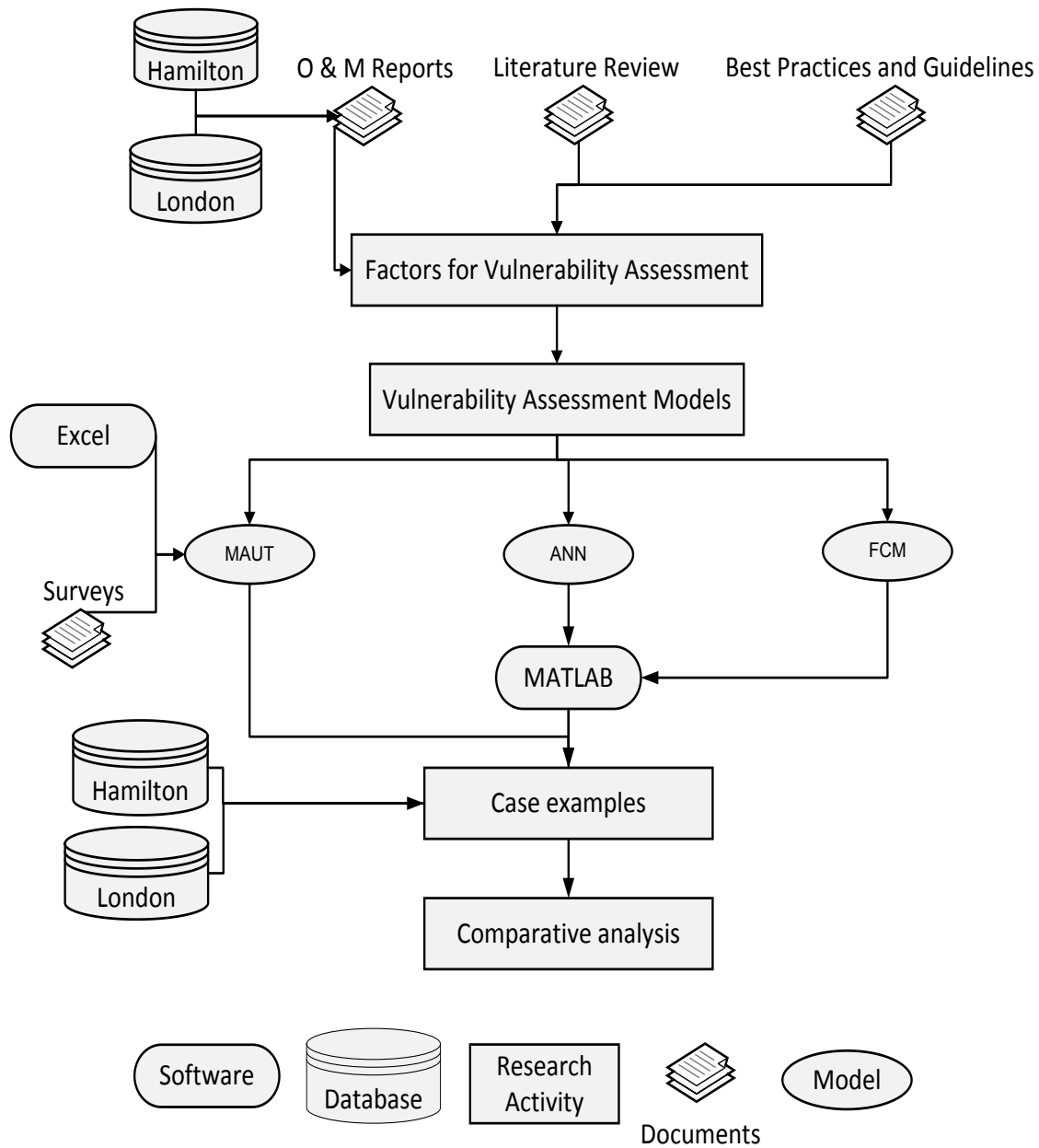


Figure 4-6 Vulnerability model overview

By examining Figure 4-7, pipe condition, neighbouring asset condition and soil condition were the most critical factors in rating spatial vulnerability for water and sewer assets. On the hand, the number and type of customers were the most critical factors in rating functional vulnerability for water and sewer assets as shown in Figure 4-8.

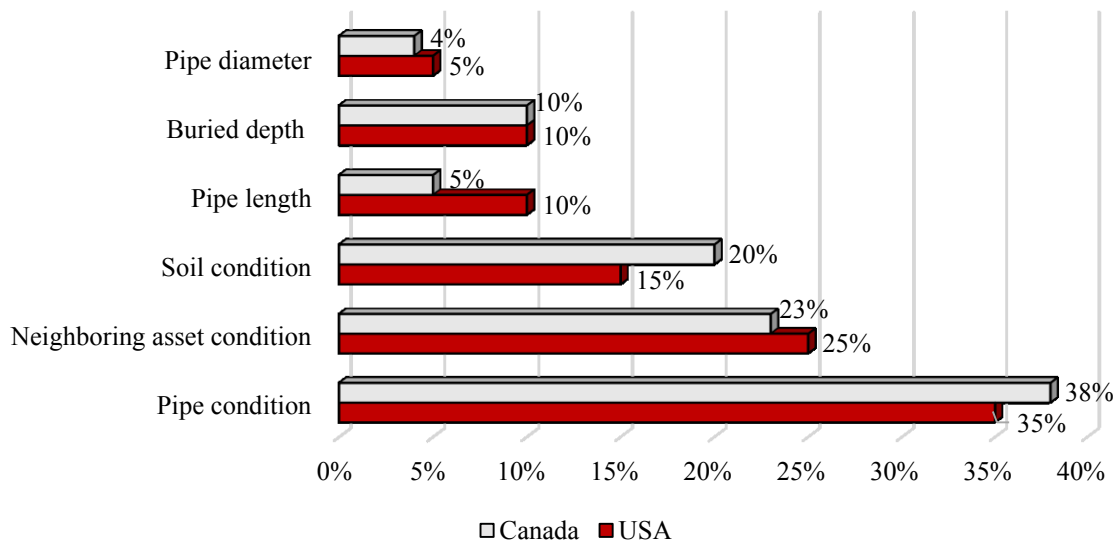


Figure 4-7 Weights of spatial factors (water and sewer assets)

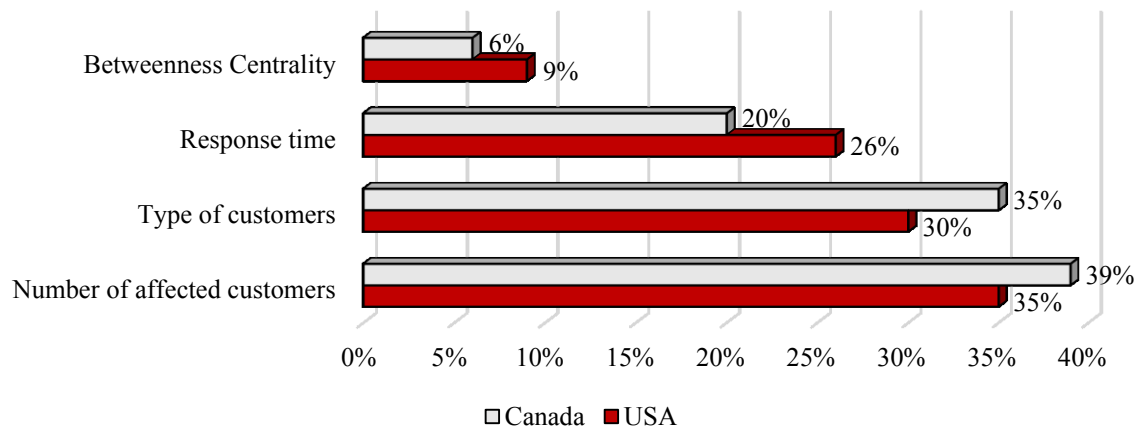


Figure 4-8 Weights of functional factors (water and sewer assets)

Figure 4-9 and Figure 4-10 show the elicited weights for spatial and functional factors of road assets. For spatial vulnerability, the most critical factors were road condition, neighbouring asset condition and soil condition. Average daily traffic, road type and response time were the most critical factors for functional vulnerability. By

examining Figures 4-7, 4-8, 4-9 and 4-10, Canadian and USA experts had similar views on assigning weights for spatial and functional factors.

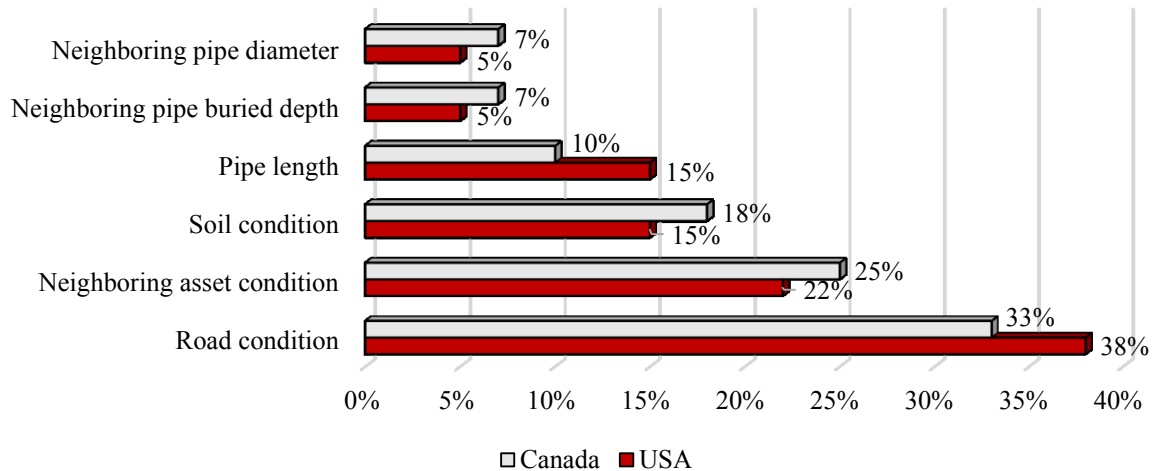


Figure 4-9 Weights of spatial factors (road assets)

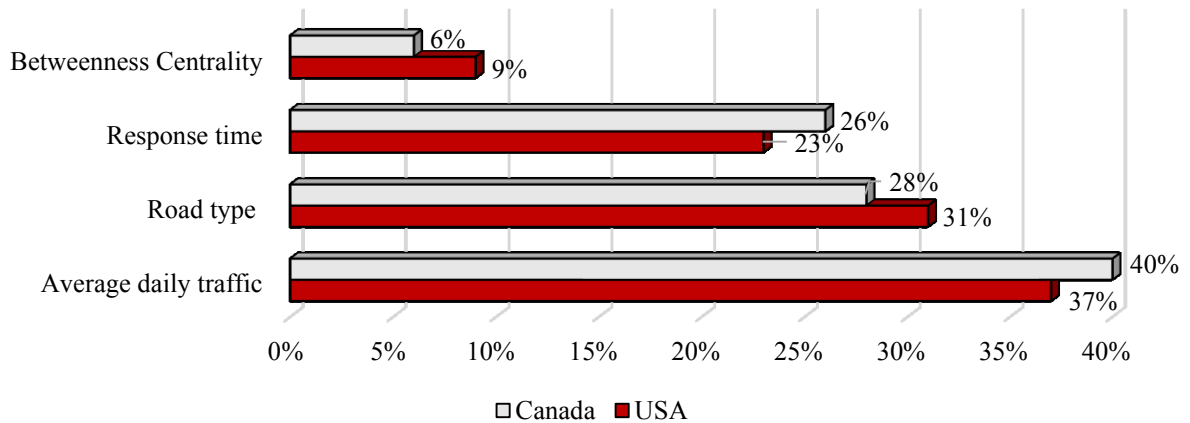


Figure 4-10 Weights of functional factors (road assets)

To construct a utility function, the highest and lowest values should be first identified and assigned arbitrary values 0 and 1, respectively. Three intermediate values are determined using experts' knowledge. The hypothetical scenarios are identified and

then the experts were asked to rate their satisfaction over a range of achievement levels on each factor. The developed utility functions are shown in Appendix B. The overall vulnerability rating of an asset is determined using the following equation (Moselhi and Martinalli, 1994):

$$U_i = \sum_{j=1}^n W_j * U_{ij} \dots\dots\dots \text{Equation 4-5}$$

Where  $W_j$  is the weight assigned to factor  $j$ ,  $U_{ij}$  is the utility score for the  $j^{\text{th}}$  factor associated with the  $i^{\text{th}}$  asset.

#### 4.3.2 ANN

Self-organizing map (SOM) is a type of ANN that is trained using unsupervised learning to produce a two-dimensional discretized representation of the input space called a map (Andrieu et al., 2003). SOMs are different from other ANNs in the sense that they use a neighborhood function to preserve the topological properties of the input space (Bishop, 2006). SOM consists of components called neurons and associated with each neuron are a weight vector of the same dimension as the input data vectors, and a position in the map space. The usual arrangement of nodes is a two-dimensional regular spacing in a hexagonal or rectangular grid. The generated self-organizing map describes a mapping from a higher-dimensional input space to a lower-dimensional map space. The procedure for placing a vector from data space onto the map is to find the node with the closest (smallest distance metric) weight vector to the data space vector. The developed ANN algorithm is shown in Figure 4-11 and it can be summarized into 5 steps:

1. Randomize the map's nodes weight vectors.

2. Select an input vector  $D(t)$ .
3. Traverse each node in the map
  - a) Use the Euclidean distance to find the similarity between the input vector and the selected node's weight vector.
  - b) Track the node that produces the smallest distance; this node is the best matching unit (BMU).
4. Update the nodes in the neighborhood of the BMU (including the BMU itself) by pulling them closer to the input vector.
 
$$W_v(s+1) = W_v(s) + \Theta(u, v, s) \alpha(s)(D(t) - W_v(s)) \dots \dots \dots \text{Equation 4-6}$$
5. Increase  $s$  and repeat from step 2 while  $S < \lambda$

Where  $S$  is the current iteration,  $\lambda$  is the iteration limit,  $t$  is the index of the target input data vector in the input data set  $D$ ,  $D(t)$  is a target input data vector,  $v$  is the index of the node in the map,  $W_v$  is the current weight vector of node  $v$ ,  $u$  is the index of the best matching unit (BMU) in the map,  $\Theta(u, v, s)$  is a restraint due to distance from BMU, usually called the neighborhood function, and  $\alpha$  is a learning restraint due to iteration progress.

### 4.3.3 FCM

Fuzzy c-means (FCM) is a data clustering technique where each data point belongs to a cluster with some degree that is specified by a membership grade (Zhu et al., 2005). This technique was originally introduced by Jim Bezdek in 1981 as an improvement on earlier clustering methods (Bezdek, 1981).

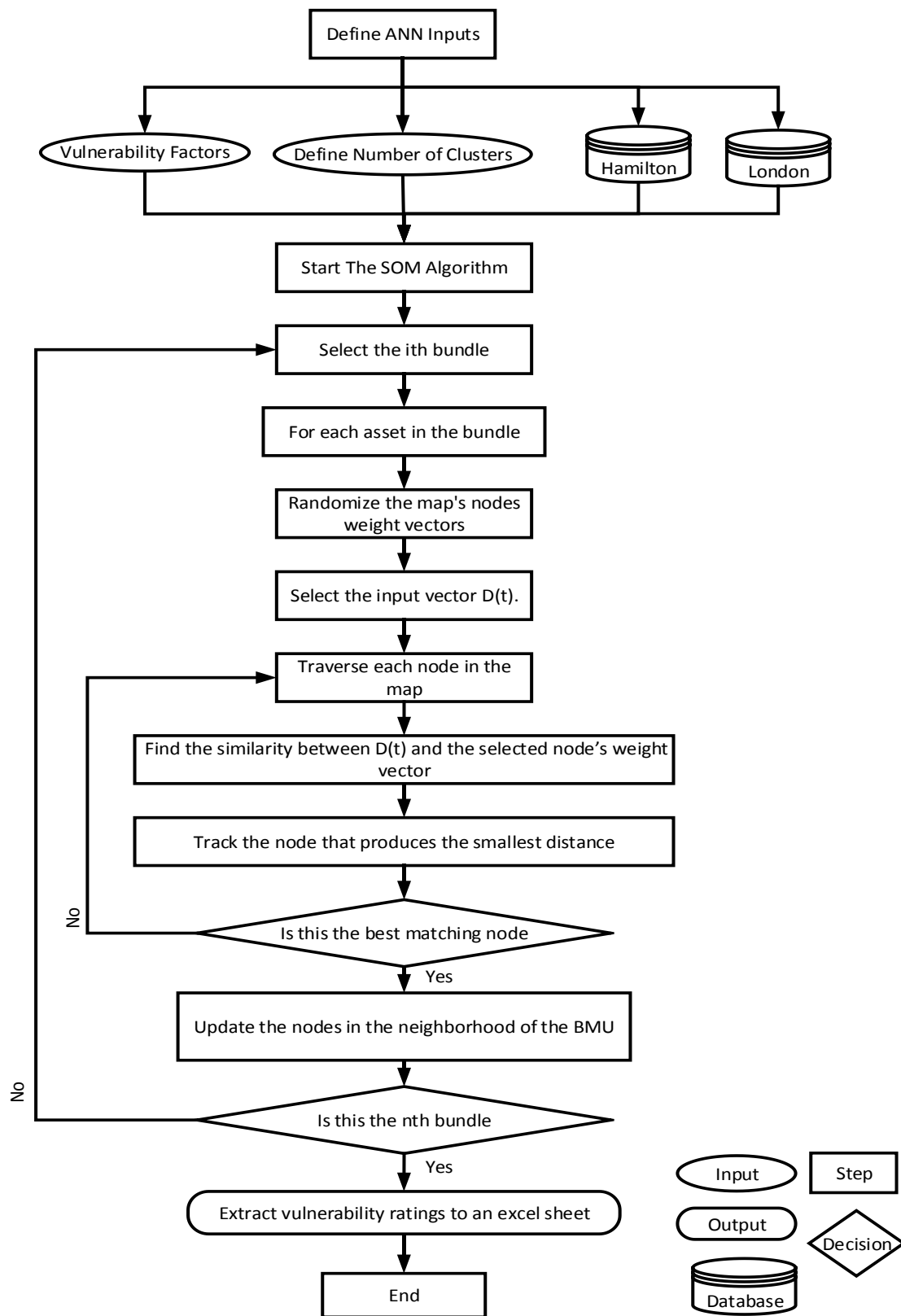


Figure 4-11 The developed ANN algorithm



It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. More details about the FCM implementation can be found in (Bezdek., 1981; Zhu et al., 2005 and Nock, 2006).

The FCM model starts with an initial guess for cluster centers, which are intended to mark the mean location of each cluster. The initial guess for these centers is most likely incorrect. Additionally, the FCM model assigns every dataset a membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the right location within a data set (Nock, 2006 and MATLAB, 2013). This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade. The algorithm steps are shown in Figure 4-12. These steps can be summarized as following:

1. Select the number of clusters.
2. Assign randomly to each point coefficients for being in the clusters.
3. Repeat until the algorithm has converged (that is, the coefficients' change between two iterations is no more than the given sensitivity threshold):

- a) Compute the centroid for each cluster (MATLAB, 2013).

$$W_k(x) = \frac{1}{\sum_j \left( \frac{d(\text{center}_k, x)}{d(\text{center}_j, x)} \right)^{\frac{2}{m-1}}} \dots \dots \dots \text{Equation 4-7}$$

- b) For each point, compute its coefficients of being in the clusters (MATLAB, 2013).

$$C_k = \frac{\sum_x W_{k*}(X)^{m*X}}{\sum_x W_{k*}(X)^m} \dots\dots\dots \text{Equation 4-8}$$

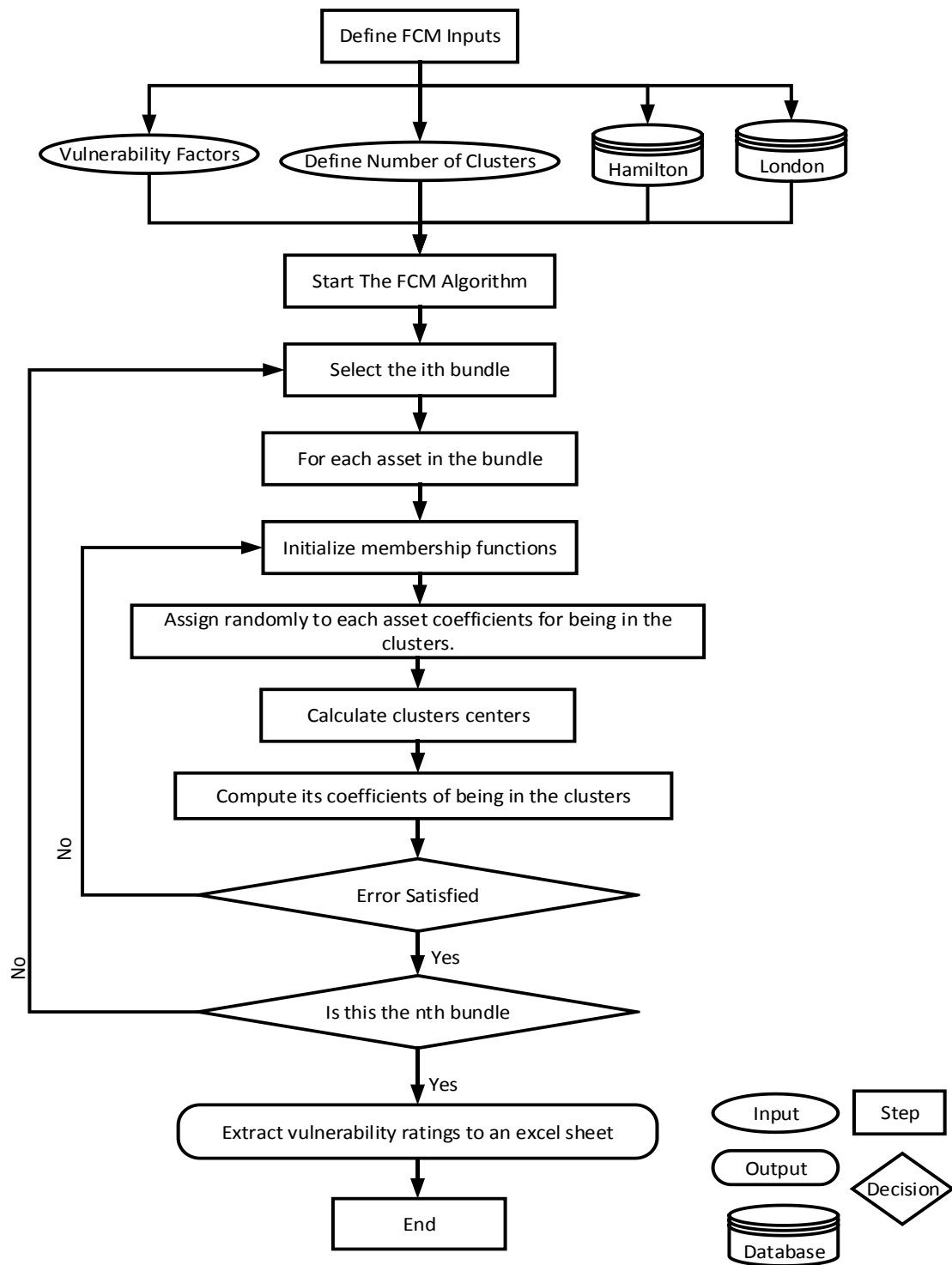


Figure 4-12 The developed FCM algorithm

## **4.4 System Dynamics Model**

### **4.4.1 System Dynamics**

SD is a modeling approach to understand strategic problems in complex dynamic systems using feedback loops and stocks flow (Sterman, 2000). The SD is utilized in this research because of its modeling elements; feedback loops and stocks flow. These feedback loops and stocks flow can capture some system dynamics that cannot be modeled by discrete event simulation or agent based modeling. Discrete event simulation is an event driven simulation paradigm focusing on modeling certain processes at their operational level. On the other hand, agent based modeling is focusing on modeling behavioral characteristics to gain some explanatory insights into the collective behavior of agents obeying set of rules (Macal and North, 2006). The SD is useful when:

1. Systems' behavior may not be predicted only by behavior of the individual parts.
2. The modeled systems are governed by feedback.
3. The systems are nonlinear and history-dependent.

These characteristics apply to the problem that is being addressed in this research. However, SD is a paradigm for understanding systems' behavior and lacks the ability of finding optimal policies to control these systems over time. Therefore, in this research system dynamics is augmented with two optimization algorithms to find optimal policies at bundle and network level. The following two sections provide an overview of SD concepts and its modeling tools to layout the foundation for detailed discussion of the developed SD model.

#### **4.4.2 Casual Loop Diagrams**

CLDs are an easy to understand diagram that represents the feedback structure of a system and they consist of variables and causal links (Sterman 2000). Variables are related by the causal links, to determine how dependent variables would change if the variables they depend on change. A positive link indicates that the dependent variable is directly proportional to the cause, so that when the cause increases (decrease) the depending variable increase (decrease) above (below) what would have been. A negative link indicates that the dependent variable is inversely proportional to the cause, so that when the cause increases (decrease) the depending variable decrease (increase) below (above) what would have been. Feedback loop is a loop of interconnected variables, such that when a variable of this loop is changed, this change propagates through the loop resulting in a change to the originating variable. When the change in the originating variable causes a change in other variables that strengthens the original process, the feedback loop is termed a reinforcing or positive feedback loop. If the change counteracts the original process, the feedback loop is termed a balancing or negative feedback loop (Rehan 2011).

#### **4.4.3 Stock and Flow Diagrams**

CLD are very useful at the beginning of the modeling process, as they can capture feedback loops of a system. However, they suffer from the inability of capturing the stock and flow behavior of the system's variables. Stock and flows (SF), along with feedback loops are two central concepts of system dynamics (Sterman 2000). Stocks represent variables with an accumulating nature, while flows represent the variables that cause the accumulations (rates of accumulation). In SFs, stocks are represented by

rectangles and flows are represented by arrows. The value of a stock variable is changed during simulation only through changes of its flow variables (inflows or outflows). Flows can originate or terminate from a stock or a cloud. Clouds represent unlimited stocks outside the boundary of the modeled system, such that they never run dry or get full.

#### **4.4.4 Causal Loops**

The causal feedback loops diagram (CLD) has 8 feedback loops as shown in Figure 4-13. Causal loops (R1 and R2) were developed based on literature and the remaining causal loops were developed based on four unstructured interviews with three experts in the domain of municipal asset management; one from the city of London and two from the city of Hamilton. While limited number of interviews (i.e. four interviews) were conducted to build the SD model, it can be used as a proof of concept on how SD can be developed and implemented to find cost effective intervention policies. Six feedback loops were constructed based on these interviews. Isaacs (1992) and Sterman (2002) presented guidelines for developing CLD using unstructured interviews. The following guidelines were utilized in this research:

1. Theme Selection: creating CLD is part of a process of articulating deeper insights about complex issues the decision maker is interested in modeling. Therefore, it is critical to determine what is being targeted by SD modeling to establish CLD. The SD model is targeting interdependent infrastructure assets modeling and the SD theme is the same as the above stated objective.

2. Time Horizon: the decision maker should determine an appropriate time horizon for the issue being modeled considering the model theme to recognize dynamics of the targeted system. In this SD model, the time horizon is in years to be capable of evaluating intervention policies at tactical and strategic level.
3. Boundary issue and level of aggregation: during the development of CLD, the decision maker should rethink of when to stop adding to CLD.

The CLD was developed on 4 stages based on the interview sessions referred to above:

- 1) Stage one – was planned to explain the basics of SD to participating experts. Causal loops such as R1 and R2 shown in Figure 4-13 were used for that purpose. R1 only depicts deterioration behavior of an asset and it was constructed from Osman et al. (2012) and Wirahadikusumah (2003). R2 depicts the effect of intervention action on 1) improving asset's condition and therefore decision maker's satisfaction from such improvement, and 2) increasing lifecycle costs due to intervention. R1 and R2 were implemented in Anylogic 7 to facilitate experts' understanding of SD basics.
- 2) Stage two – was to extract and encapsulate experts' knowledge in the development of R3 to R8 of the developed SD model. Loops R5 and R6 were developed to depict the relationship between asset's condition and its LOS. Loops R3 and R8 were developed to map the relationship between asset's condition and its vulnerability. The remaining two loops (i.e. R4 and R7) were designed to capture the satisfaction of the decision

maker based on asset's condition, LOS and vulnerability for a contemplated intervention policy.

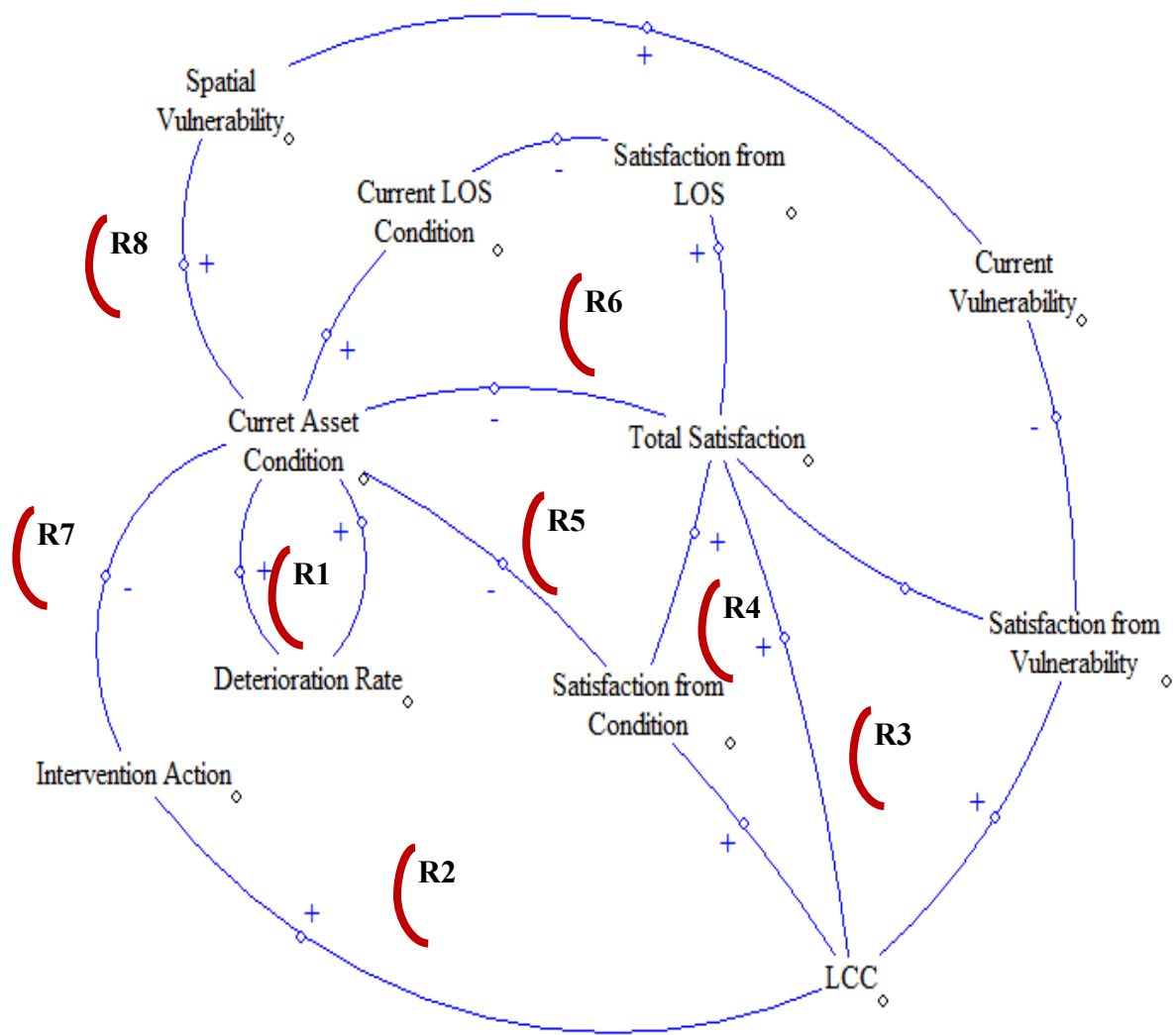


Figure 4-13 Casual Loop of the developed SD model

- 3) Stage three – was mainly to integrate the developed CLD with their related stocks flow diagram. Twenty three variables are divided into; rate variables, auxiliary variables and stock variables. The developed SD model has 5 stock variables, 8 rate variables and 10 auxiliary variables.

- 4) Stage four – focused on verification and validation with the experts; after building the CLD and integrating it with stocks flow diagram, the SD model is applied to two actual case studies and the results of the analyses were presented to the experts. The experts are asked to examine the results and based on their judgement they can suggest any modifications in CLD to obtain more realistic outcomes. Verification and validation of the developed SD model are discussed in Chapter 6.

Causal Loops from 1-4 are described subsequently. The same procedures were utilized in the development of the remaining 4 loops.

The first loop, reinforcing feedback loop R1, represents the typical deterioration process of an asset. It includes two variables; 1) the asset deterioration rate, and 2) the asset's condition. The source and purpose for each variable in R1 are shown in Table 4-1. The causality of this loop indicates that; 1) as the deterioration rate increases, the asset condition index also increases (e.g., on a scale of 1-5, where 5 is the worst condition and 1 is the best condition), 2) the increase in asset's condition is accompanied with an increase in the deterioration rate (Wirahadikusumah, 2003). The process depicted by this loop is captured by the developed algorithm shown in Figure 4-14.

Table 4-1 Sources and purposes of R1 variables

Variables	Source	Purpose
Asset condition	Geodatabase	To model asset's performance at each time step in the SD model
Deterioration rate	Road (Sarja, 2006) - Water and Sewer (Osman, 2012)	



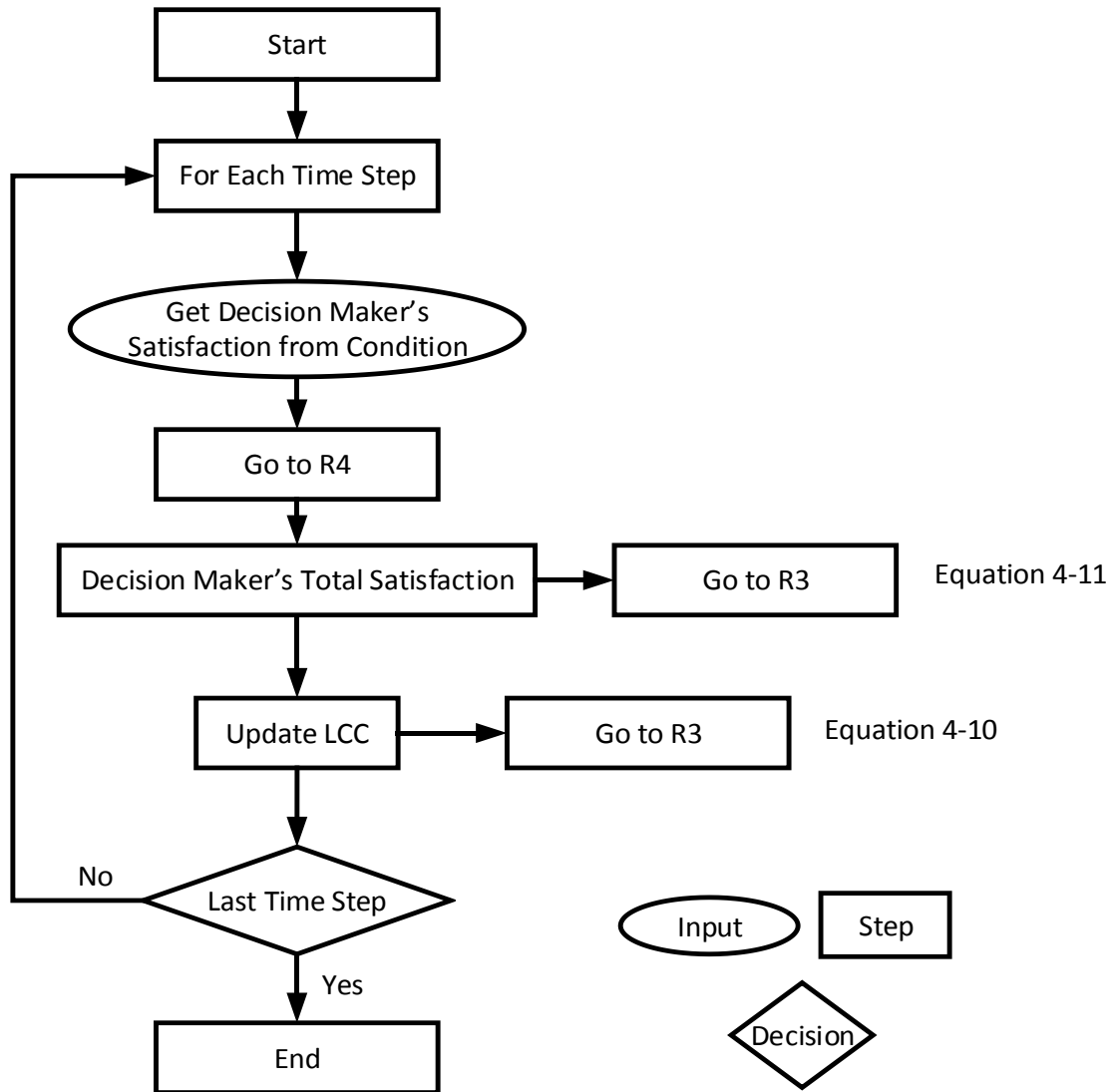


Figure 4-14 R1 algorithm

In this loop, the decision maker defines current asset's condition and its deterioration rate. For each time step and if no intervention action is applied, the algorithm decreases asset's condition by using Equation 4-9. Current asset condition is calculated using markovian model process (MDP) found in the literature (Scherer and Glagola, 1994; Abaza et al., 2004; Thomas and Sobanjo, 2013) as shown in the following equation.

$$U^t = U * T^t \dots\dots\dots \text{Equation 4-9}$$

Where U is the current asset's condition, T is the deterioration matrix and  $U^t$  is asset's condition at time step t

For example, let's assume that there is a road asset in a condition state 1 then the current condition is represented by a vector U [1 0 0 0 0]. The road asset has the following deterioration matrix (T) from (Sarja et la., 2006):

$$T = \begin{bmatrix} 0.61 & 0.39 & 0 & 0 & 0 \\ 0 & 0.74 & 0.26 & 0 & 0 \\ 0 & 0 & 0.82 & 0.18 & 0 \\ 0 & 0 & 0 & 0.91 & 0.09 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

When using R1 to predict the asset condition for the next 50 years, it will generate the following deterioration curve shown in Figure 4-15. If an intervention action is applied, the SD model will go to R2 loop.

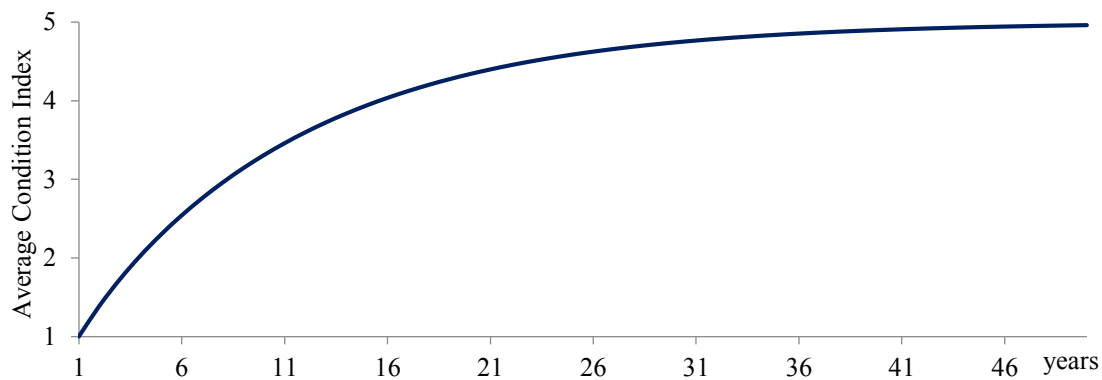


Figure 4-15 Deterioration curve for the road asset

Loop number 2, reinforcing feedback loop R2, represents the effect of intervention action on asset's condition, LCC and decision maker's satisfaction from

current condition. It includes four variables; 1) intervention action, 2) asset's condition, 3) LCC, and 4) decision maker's satisfaction from condition. The source and purpose for each variable in R2 are shown in Table 4-2 except for asset's condition which was shown in Table 4-1. The causality of this loop indicates that; if an intervention action is taken, the asset's condition increases, LCC increases as well and decision maker's satisfaction from asset's condition will increase. The process depicted by this loop is captured by the developed algorithm shown in Figure 4-16 .

Table 4-2 Sources and purposes for R2 variables

Variables	Source	Purpose
Intervention actions	(Hashemi et al, 2008)	To improve asset's performance
Intervention actions cost	(Hashemi et al, 2008)	To calculate LCC at each time step of the SD
Satisfaction from condition	Decision maker (assumed)-discussed with the experts	To measure decision maker's satisfaction for having an asset in a certain condition

In this loop, the decision maker defines available intervention actions and their associated costs as shown in Table 4-2. The decision maker needs also to define a utility function to measure his satisfaction from having an asset in a certain condition. First, the decision maker identifies highest and lowest satisfaction points for asset's condition. Three intermediate satisfaction points are defined subsequently. Figure 4-17 shows an example of the utility function developed with the experts to represent decision maker's satisfaction from the road condition. In this figure, the target condition in for the road assets is 2. If current asset's condition is equal to this target condition, the decision maker will be fully satisfied. If not, the decision maker's satisfaction will decrease according to Figure 4-17.

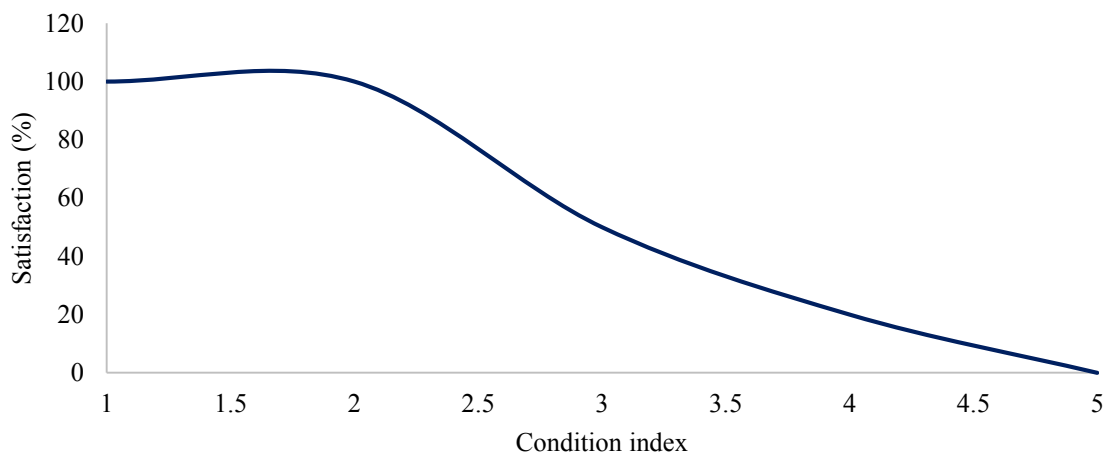
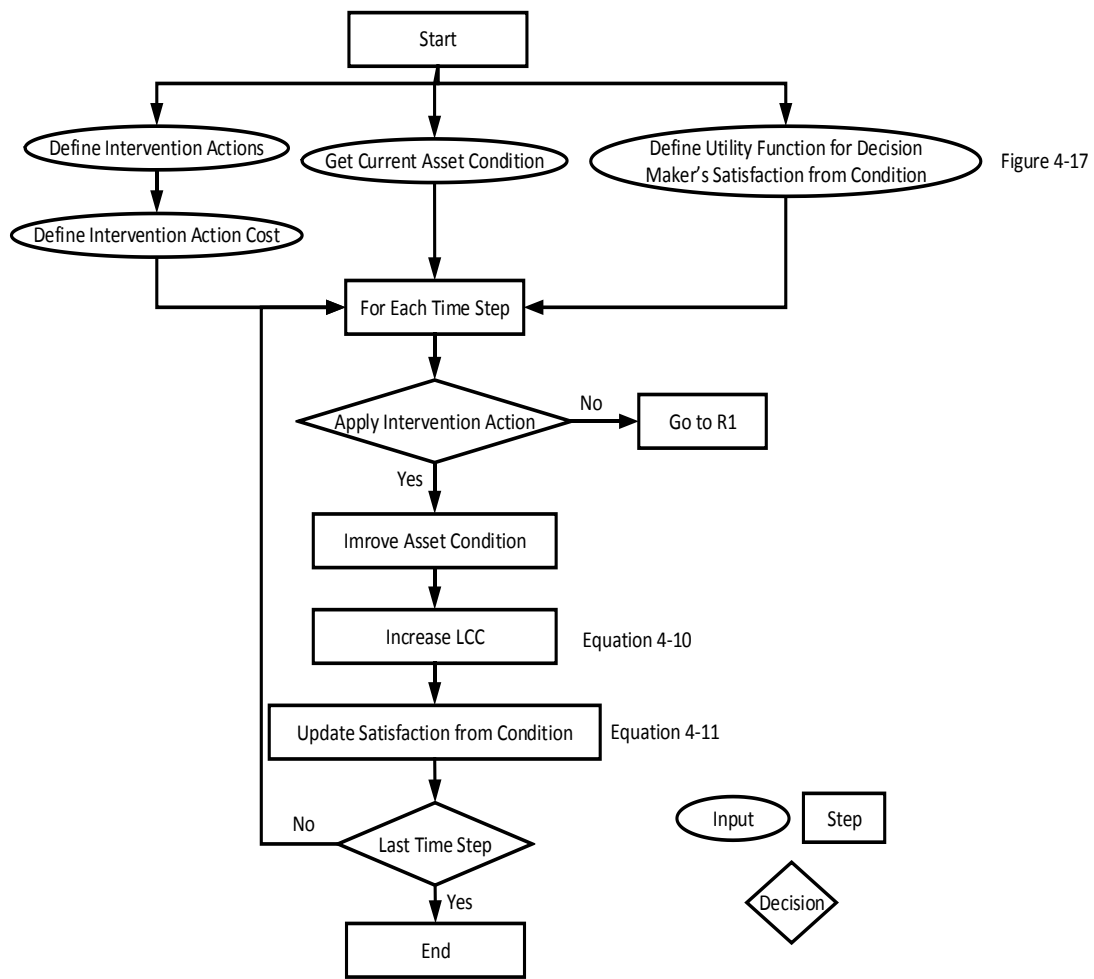


Figure 4-17 Decision maker's satisfaction from road condition

The SD model is generic by allowing decision makers to define their utility functions or use the functions defined by the experts in the unstructured interviews. When asset's condition changes at each time step, the new score for decision maker's satisfaction from current condition is calculated and is sent to Loop R3 to calculate decision maker's total satisfaction from current asset's condition, its LOS and its vulnerability.

Each intervention action will improve asset's condition by a certain percentage called intervention rate. For example, in Figure 4-18, asset's condition improves by 100% each time a replacement action is taken. Each applied intervention action will have an associated cost which is added to the current lifecycle cost (LCC) as shown in Equation 4-10.

$$LCC = I_{cost} + \int_{t=0}^{t=n} LCC \cdot dt \dots\dots\dots \text{Equation 4-10}$$

Where  $I_{cost}$  is the intervention cost,  $t$  is the simulation time and  $n$  is the current time step

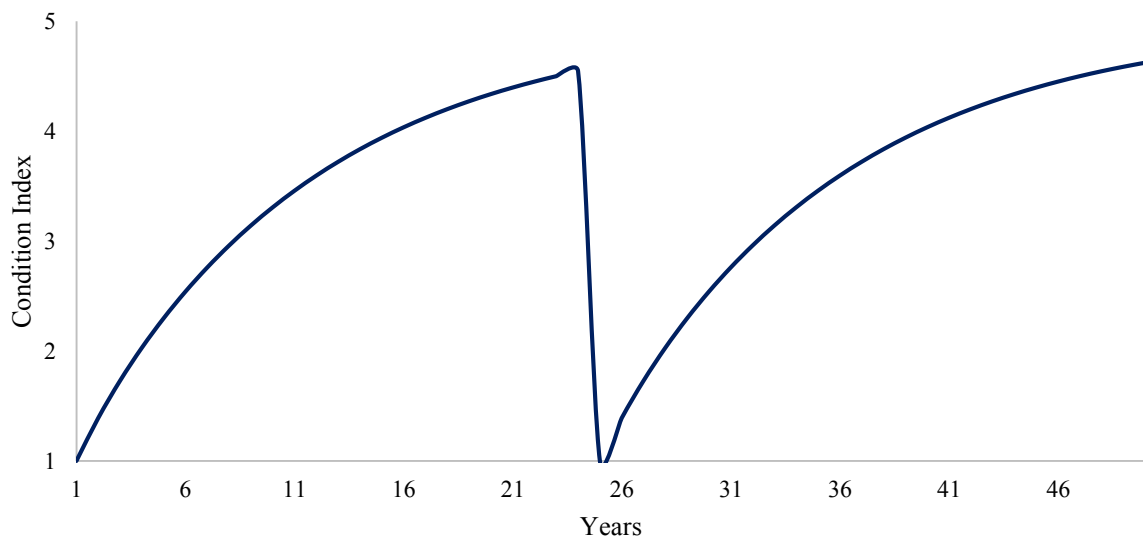


Figure 4-18 Effect of intervention action on road's condition

The effect of intervention action on the decision maker's satisfaction based on the above deterioration curve is shown in Figure 4-19. In this figure, the decision maker's satisfaction is restored to 100 % when the asset is replaced after 25 years.

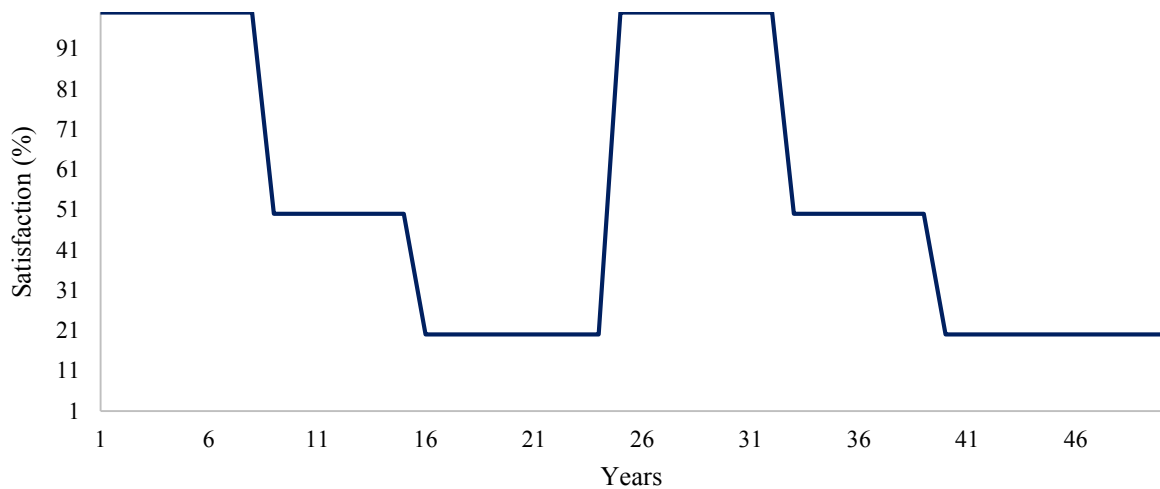


Figure 4-19 Effect of the intervention action on the decision maker's satisfaction from to road's condition

The third casual feedback loop includes three variables; 1) LCC, 2) decision maker's satisfaction from vulnerability, 3) decision maker's total satisfaction. The causality of this loop indicates that; if the decision's maker satisfaction from vulnerability increases, then decision maker's total satisfaction increases and LCC also increases. The source and purpose of each variable in this loop and next loop as well are shown in Table 4-3. An example for the decision maker's satisfaction from asset's vulnerability is shown in Figure 4-20.

Table 4-3 Sources and purposes of R3 and R4 variables

Variables	Source	Purpose
Vulnerability rating	From FCM model	To rationale intervention polices based on asset's vulnerability.
Level of service (LOS)	Assumed (correlated with condition- i.e. linear, exponential...etc.)	To rationale intervention polices based on asset's LOS.
Weight of decision maker's satisfaction from condition	The experts or defined by decision maker	To decide the importance of improving decision maker's satisfaction from asset's condition, its LOS and its vulnerability
Weight of decision maker's satisfaction from LOS	The experts or defined by decision maker	
Weight of decision maker's satisfaction from vulnerability	The experts or defined by decision maker	
Total satisfaction	Equation 4-11	To rationale intervention polices based on asset's condition, its LOS and its vulnerability.

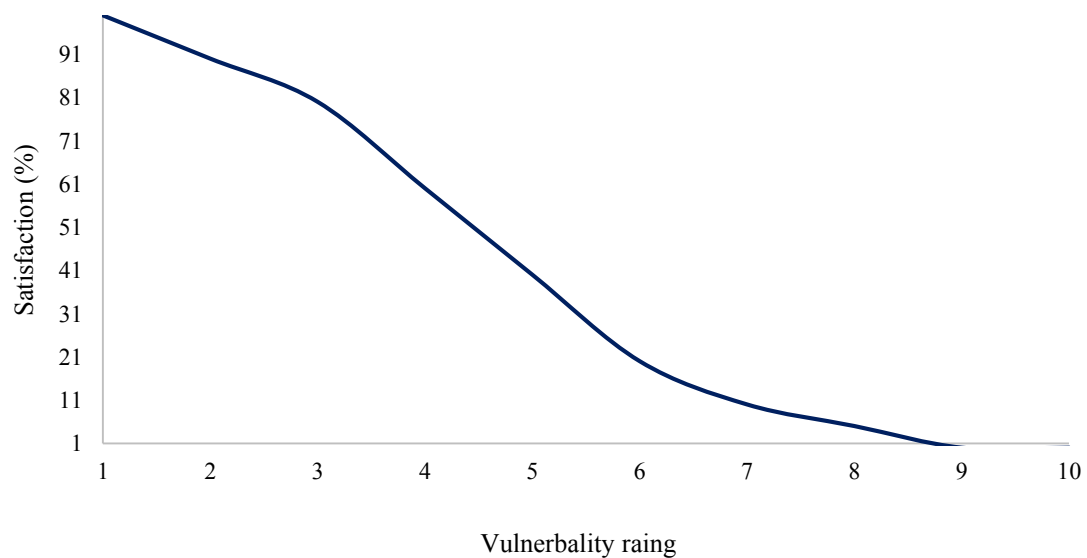


Figure 4-20 Decision maker's satisfaction from vulnerability of road assets

This utility function is established using the same procedure illustrated in R2. The algorithm that depicts this process is shown in Figure 4-21. At each time step, the algorithm aggregates decision maker's satisfaction because of current asset's condition (R4), its LOS (R6) and its vulnerability (R8). The algorithm uses Equation 4-11 to calculate the decision maker's total satisfaction.

$$Tst = Wc * Cst + W_{LOS} * LOSst + W_{VL} * VLst \dots\dots\dots \text{Equation 4-11}$$

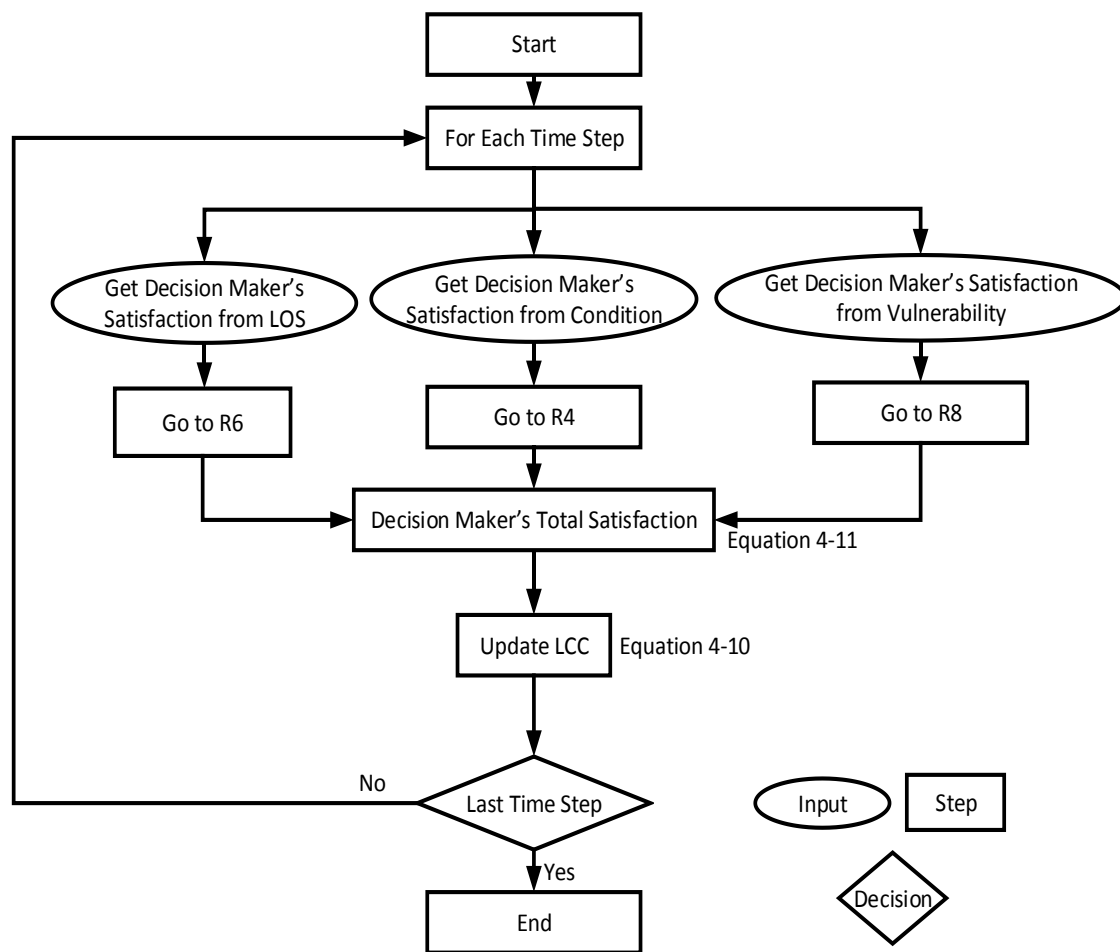


Figure 4-21 R3 algorithm

Where Tst is the total satisfaction, Wc is the weight for satisfaction from asset's condition, Cst is decision maker's satisfaction for current condition, W<sub>LOS</sub> is the weight



for satisfaction from LOS,  $LOS_{st}$  is decision maker's satisfaction for current LOS,  $W_{VL}$  is the weight for satisfaction from current vulnerability,  $VL_{st}$  is decision maker's satisfaction for current vulnerability.

The fourth casual feedback loop includes three variables; 1) LCC, 2) decision's maker satisfaction from condition, 3) total satisfaction. The causality of the loop indicates that; if decision maker's satisfaction from asset's condition increases, then decision maker's total satisfaction increases and LCC also increases. The algorithm that depicts this process is shown in Figure 4-22.

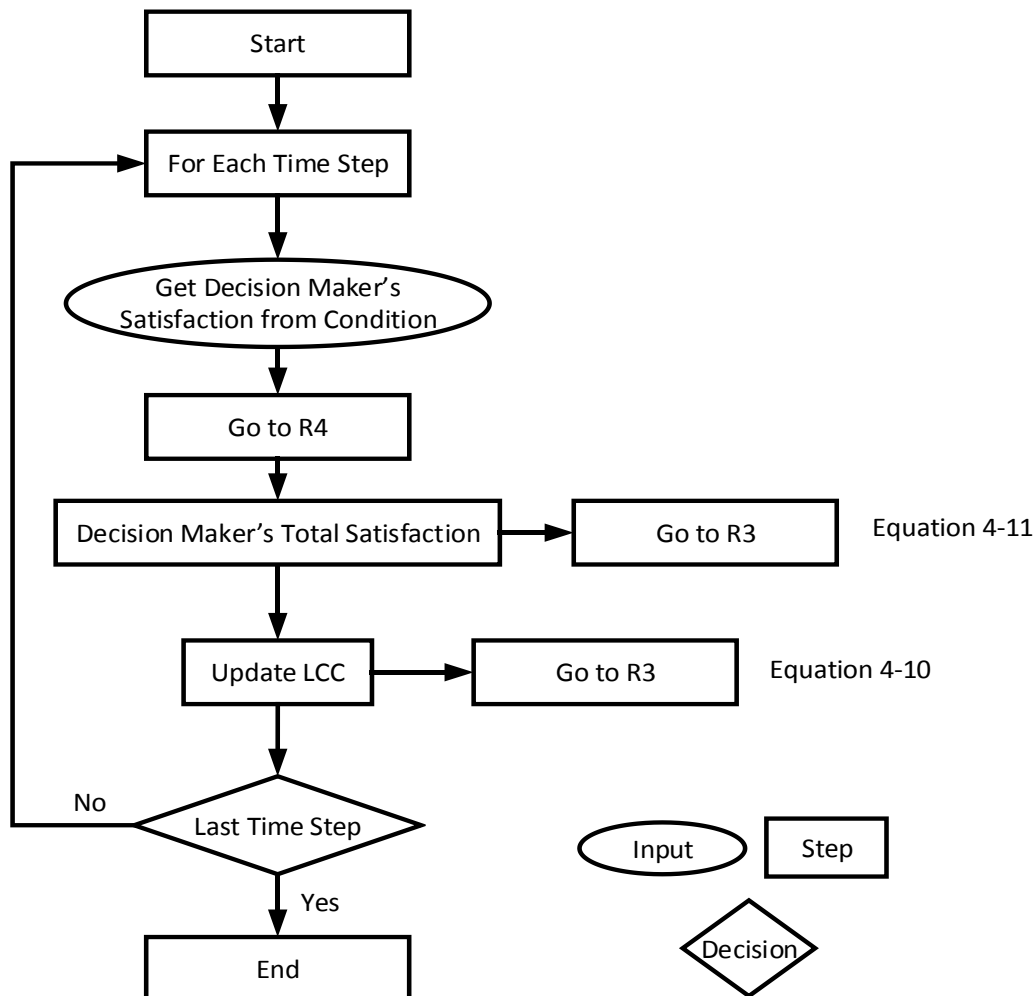


Figure 4-22 R4 algorithm

At each time step, the algorithm obtains decision maker's satisfaction for asset's condition (R4). The algorithm then sends this value as an input for R3 to calculate decision maker's total satisfaction using Equation 4-10. R6 and R8 have similar structure to R4. Next section explains how the developed CLD was integrated with stocks flow diagram and describes as well the mathematical equations used to represent CLD.

#### 4.4.5 Stock and Flow

The stocks flow diagram combined with the causal feedback loops is shown in Figure 4-22. The SD Variables are modeled as stocks if the SD is performing actions based on the history of such variables. Five variables were represented as stocks, asset's condition, asset's LOS, asset' vulnerability total satisfaction, and LCC, as shown in Figure 4-23. The following steps are repeated over the simulation time interval for each asset in the bundle:

1. At each time step, current asset condition is calculated using R1.
2. The SD model checks if asset's condition, its LOS and its vulnerability are within the target and trigger constrains defined by the decision maker. These constrains are defined by the decision maker to evaluate feasibility of each policy.

$$L_u < U < T_u \dots \dots \dots \text{Equation 4-12}$$

$$L_{LOS} < LOS < T_{LOS} \dots \dots \dots \text{Equation 4-13}$$

$$L_{VL} < VL < T_{VL} \dots \dots \dots \text{Equation 4-14}$$



Where  $L_u$  is the trigger asset condition,  $T_u$  is the target asset condition,  $L_{LOS}$  is the trigger LOS,  $T_{LOS}$  is the target LOS,  $L_{VL}$  is the trigger vulnerability,  $T_{VL}$  is the target vulnerability

3. It should be noted that the vulnerability model is embedded as an object inside the SD model to facilitate computing of asset's vulnerability due to changes occurred by other SD variables at each time step. Also, LOS is assumed to be correlated (i.e. linearly, exponentially ...etc.) with asset's condition due to lack of historical records that can be used for depicting such relationship.
4. The SD model applies available intervention actions at each time step to improve asset's condition, LOS and vulnerability. Each applied action will cause an associated satisfaction gain to the decision maker based on current asset's condition, its LOS and its vulnerability. The decision maker's total satisfaction at each time step is calculated using loops R2 to R8.
5. Each applied intervention action will have an associated cost which is added to the current lifecycle cost (LCC) using Equation 4-10.

#### **4.4.6 Dynamic Programming Algorithm**

In the developed SD model, decisions are taken recursively over several points in time. Dynamic programming is suitable for such optimization problems (Hiller and Lieberman, 2005; Taha, 2005). In dynamic programming, the optimization problem is simplified by breaking it down into simpler subproblems which can be solved in a recursive manner. Detailed discussion about dynamic programming can be found in (Hiller and Lieberman, 2005; Taha, 2005). The dynamic programming algorithm is

integrated with SD to; 1) find and rank the best n solution and present these solutions to the decision maker in excel report, 2) use the ranked n solutions to seed the initial population of the SOGA.

The developed dynamic programming algorithm is shown in Figure 4-24. At the bundle level, the main objective is to maximize decision maker's total satisfaction gained from interdependent assets at each time step as shown in Equation 4-15. The decision variable in this algorithm is the combination of intervention actions to be selected at each time step to maximize Equation 4-15. Constrains are shown previously in Equations 4-12, 4-13 and 4-14.

$$V_i(T_s) = \max (\sum(T_s(w) + T_s(s) + T_s(r))) \dots\dots\dots \text{Equation 4-15}$$

Where  $V_i(T_s)$  is decision maker's total satisfaction due to certain combination of intervention actions at time step n for water, sewer and road assets and  $T_s(w,s,r)$  is the decision maker's total satisfaction for water, sewer and road assets.

Decision maker's total satisfaction from each asset is obtained using Equation 4-10 as shown in previous section. The optimization is performed by defining a sequence of value functions  $V_1, V_2, \dots, V_n$ , with an argument  $y$  representing the state of the system at each time step. These value functions represent decision maker's total satisfaction obtained from interdependent assets in each bundle. Using backward calculations, these value functions ( $V_i$ ) at earlier time steps ( $i = n - 1, n - 2 \dots 2, 1$ ) are found by using the recursive relationship shown in Equation 4-15.

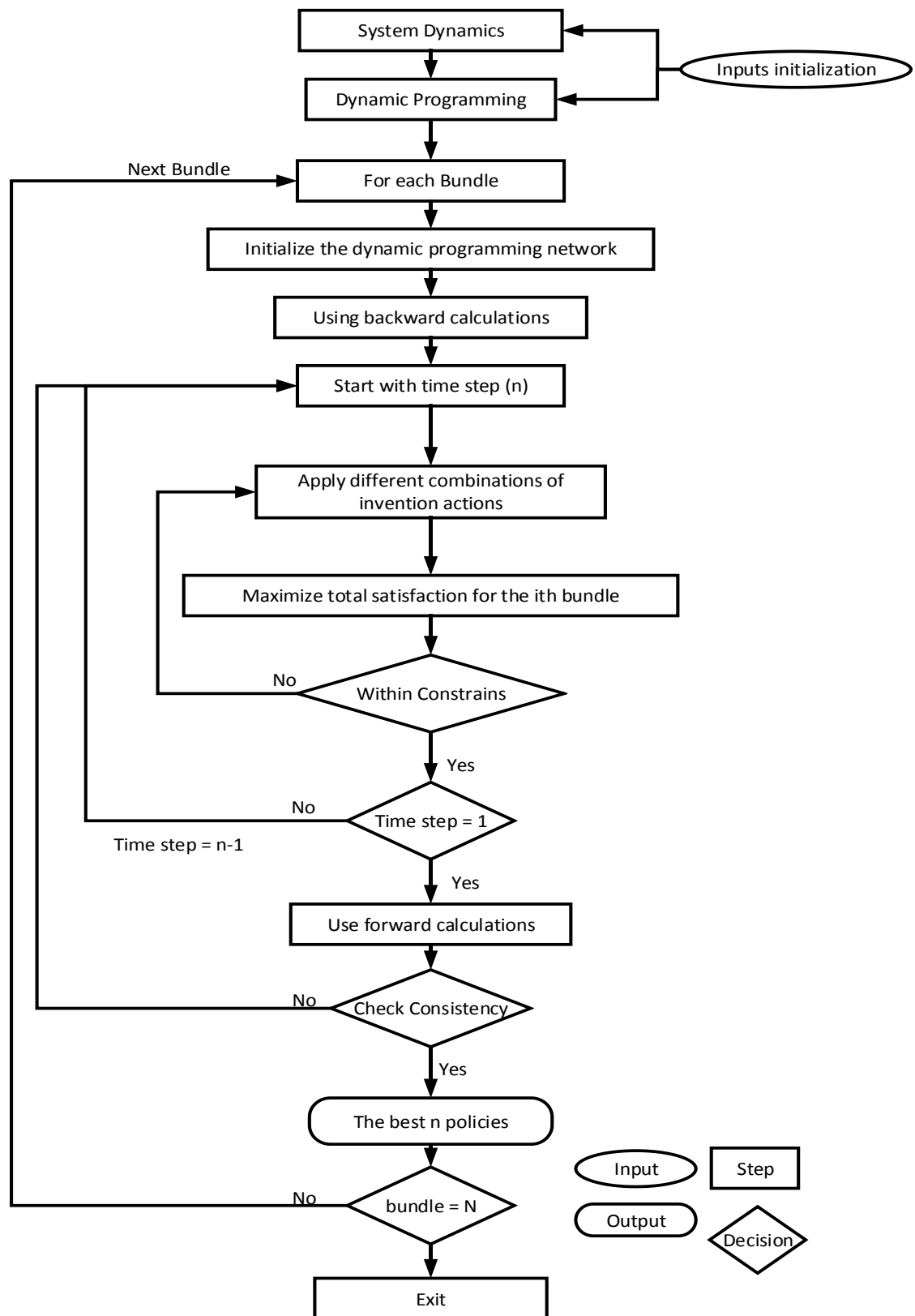


Figure 4-24 The developed dynamic programming algorithm

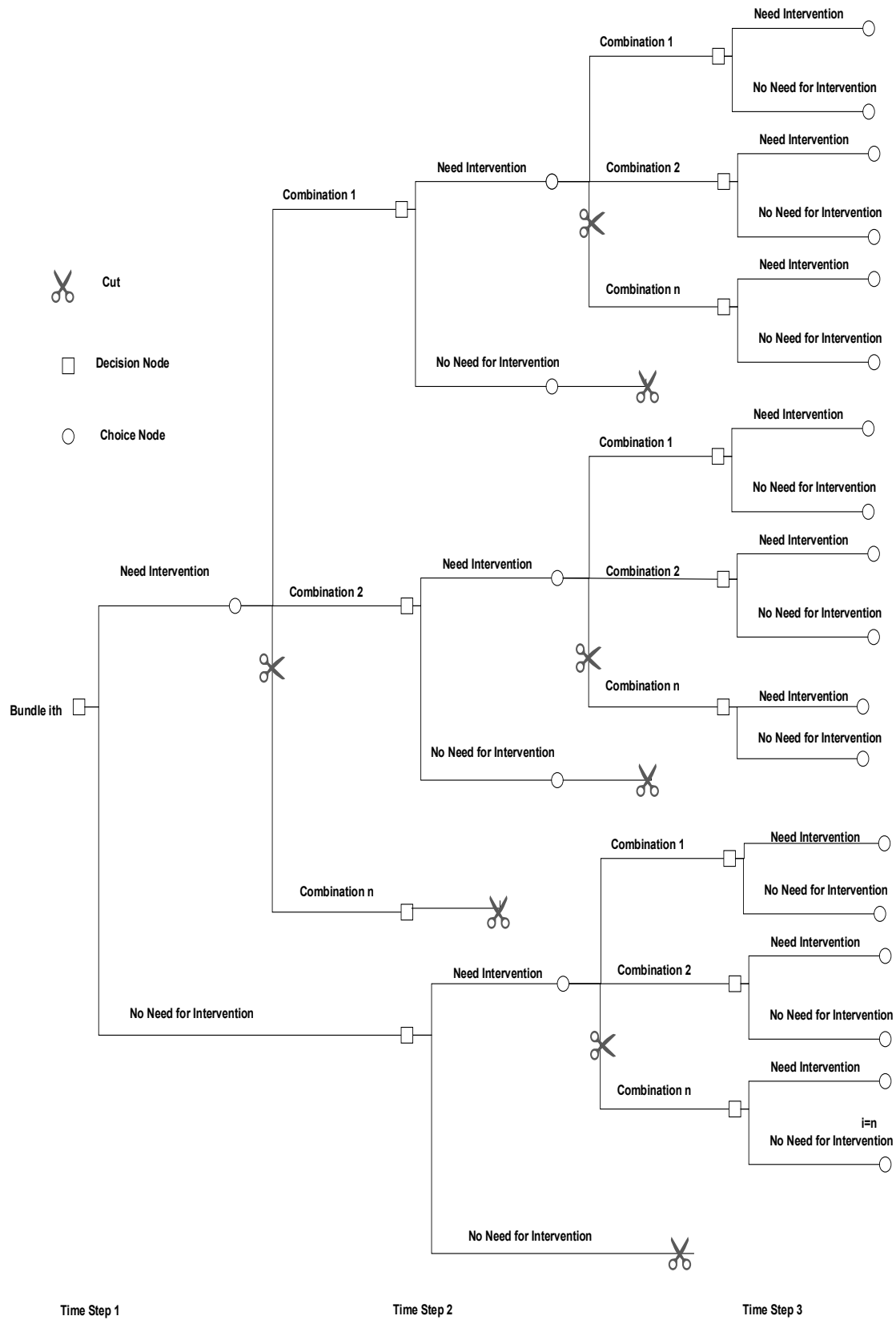


Figure 4-25 Sample of the dynamic programming network

The algorithm evaluates all possible combinations of intervention actions for each bundle to maximize Equation 4-15 within the SD model constraints (Equations 4-12, 4-13 and 4-14) as shown in Figure 4-25. The algorithm selects combination of intervention actions that maximizes Equation 4-15 in this step and previous step as well. The same steps are repeated from time step  $i=n$  to  $i=1$ . The algorithm repeats the same procedures but using forward calculations to check for consistency of obtained solutions. Finally, the dynamic programming algorithm generates the best  $n$  policies for each bundle in excel report. The inputs and the outputs of this model are shown in Tables 5-2 and 5-3 in Chapter 5.

#### **4.4.7 Single Objective Optimization Algorithm**

SOGA is an evolutionary process for improving characteristics of the off-springs based on the characteristics of their parents (Goldberg 1989). Interdependent infrastructure systems are considered as large scale systems that require near optimal solutions satisfying decision makers' objectives in reasonable computational time. Hence, non-exact methods prevail when the objective is to find near optimal solutions over large space of water, sewer and road assets. The literature review covered four non-exact algorithms like tabu search, local search strategy, simulated annealing and genetic algorithms. SOGA seems suitable as an optimization technique over other non-exact algorithms covered in Chapter 2 (Talbi, 2009; Taha, 2008; Hillier and Lieberman, 2004). It allows for exploration of wide search space in timely fashion and utilizes genetic operators to improve characteristics of search space (Talbi, 2009). Three modifications are introduced to SOGA to suite the SD model; 1) integrating a query based filtering function into the SOGA to cluster similar bundles, 2) adding dynamic memory to store



worst solutions to prevent regenerating such solutions in next iterations and 3) modifying the behavior of the mutation function to improve convergence rate of the SOGA.

In SOGA algorithm, each chromosome represents a solution containing a set of possible intervention policies for bundles at the network level as shown in

Figure 4-26. Each gene in the chromosome represents an intervention policy for a certain bundle and each policy contains set of intervention actions taken at each time step for that bundle. The policy inside each gene is selected randomly for the best n ranked alternatives computed by the SD and dynamic programming algorithm. The inputs and outputs of the SOGA are shown in Tables 5-4 and 5-5.

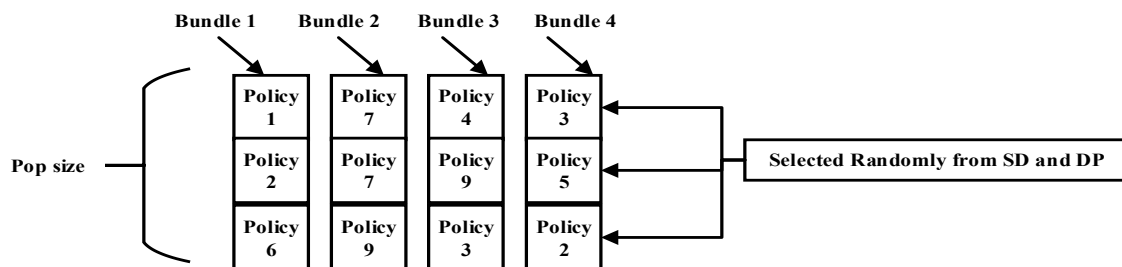


Figure 4-26 Chromosome structure

The objective of this algorithm is to maximize the decision maker's satisfaction from each bundle at network level by applying a set of intervention policies.

$$Z = \max (\sum_i^n (\sum (Ts(w)+ Ts(s)+ Ts(r)))) \dots\dots\dots \text{Equation 4-16}$$

Where Z is the objective and n is the ith bundle

Reproducing a new population is performed by utilizing crossover and mutation until convergence is reached as shown in Figure 4-27.

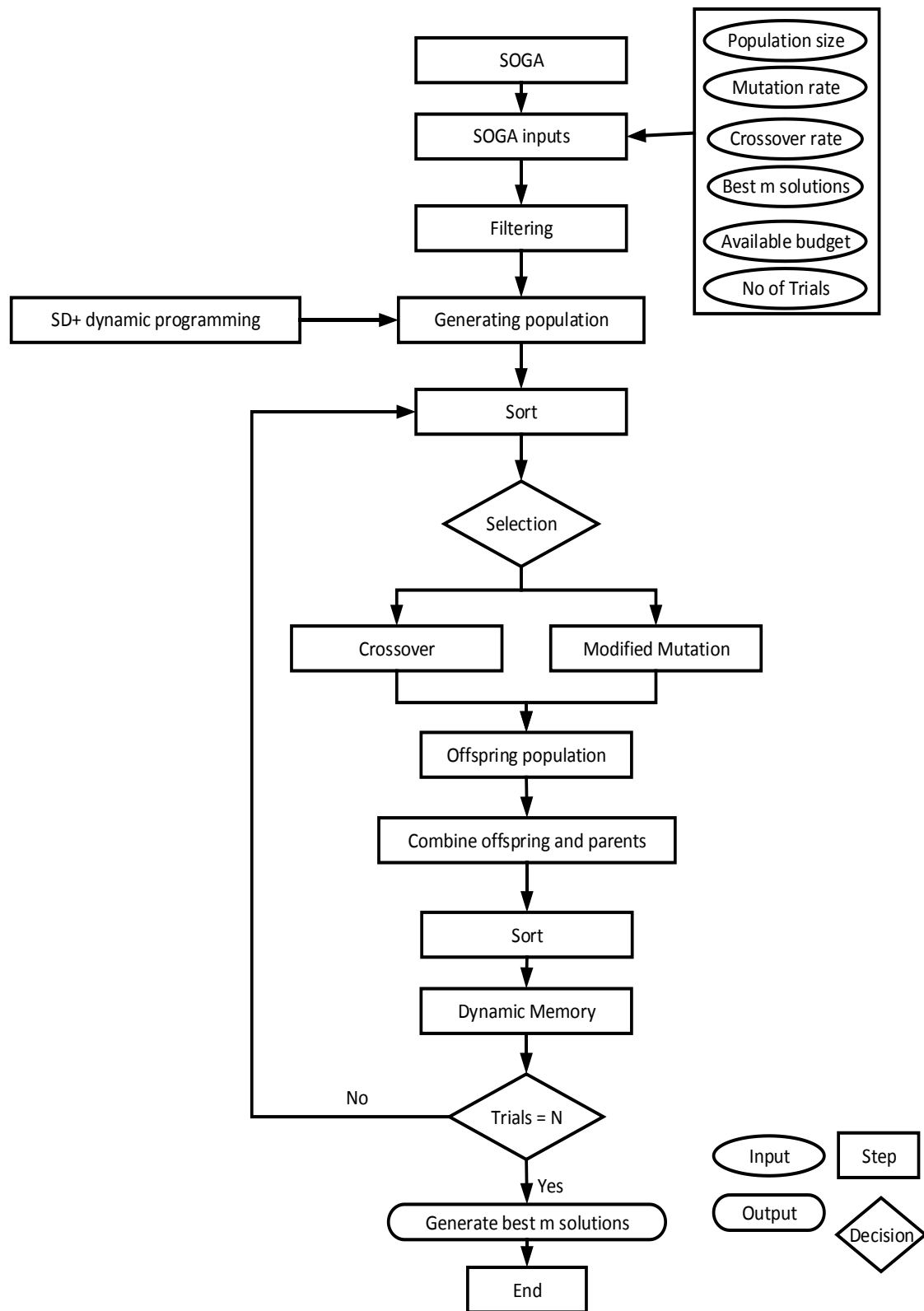


Figure 4-27 The developed SOGA algorithm

This optimization algorithm has the same constraints shown in Equations 4-12, 4-13 and 4-14. The algorithm is also constrained by finding a near optimum policy for analyzed bundles within budget constraints.

$$B_{\text{allocated}} < B_{\text{assigned}} \dots\dots\dots \text{Equation 4-17}$$

Where  $B_{\text{allocated}}$  is available budget and  $B_{\text{assigned}}$  is assigned budget

The single objective genetic algorithm is enhanced by:

1. Integrating a query based filtering function into the SOGA. The filter function will use query language of the database management systems (DBMSs) to cluster similar bundles. For example, several bundles may have the same assets' characteristics; condition, LOS, vulnerability. To facilitate the SOGA analysis, only one of these similar bundles will be considered in building the SOGA chromosomes.
2. Adding a dynamic memory that stores worst solutions. This will insure that such solutions will not be regenerated in subsequent trials of the SOGA and hence increase the fitness of future generations. The memory is dynamic because it is updated at each trial of the SOGA with worst solutions.
3. Changing behavior of the mutation function in the SOGA. In traditional genetic algorithm, the mutation function improves chromosome's fitness by randomly changing only one of its genes. The modified mutation function will perform the following:
  - a) One of the chromosome's genes will be randomly selected.

- b) The algorithm will check if by changing the selected gene, the new chromosome's fitness does improve. If not, a new gene is selected and procedures a and b are repeated again.
- c) The algorithm will repeat step a and b until no further improvement can be obtained for this selected chromosome or the solution become infeasible.
- d) The decision maker can define a threshold for the number of iterations used in the mutation function in order to improve chromosome's fitness. This will help in preventing infinite loops.

## **4.5 Summary and Conclusion**

In this chapter, three developed models were described for optimizing intervention policies for likely vulnerable civil infrastructure networks considering their spatial and functional interdependencies. The first model was the interdependency model which consists of two modules; spatial module and functional module. The first identifies which assets are spatially interdependent using ArcGIS geoprocessing tools. The second identifies asset's connectivity with its network and hence understand to what extent it can compromise the performance of their respective networks. The vulnerability model consists of three computational models; 1) MAUT, 2) ANN and 3) FCM. MAUT: The MAUT model relies extensively on experts' judgment in assessing vulnerability of interdependent assets. Unlike the MAUT model, the ANN model doesn't require extensive feedback from experts to establish a vulnerability assessment model. Instead, the ANN model utilizes the recognized patterns in each dataset to assess vulnerability of interdependent assets. On the other hand, the FCM model accounts for

ambiguity that arises due experts' judgement in rating vulnerability of interdependent assets. Finally, the SD model was presented to allocate intervention actions at both bundle and network levels. The developed SD consists of 23 variables and 8 causal feedback loops which were extracted and constructed based on extensive literature review and four unstructured interviews with official members from City of London. At the bundle level, the SD model is supplemented with dynamic programming algorithm for finding and ranking best  $n$  intervention policies. At the network level, the SD is supplemented with genetic algorithm to find and rank the best  $m$  near optimal intervention policies. The SOGA considers the  $n$  ranked policies identified by the dynamic programming algorithm to seed its initial population. The single objective genetic algorithm is modified by; 1) integrating a query based filtering function into the SOGA to cluster similar bundles, 2) adding dynamic memory to store worst solutions to prevent the regeneration of such solutions in next iterations and 3) modifying the behavior of the mutation function to improve the convergence rate of the genetic algorithm.

# Chapter 5 : COMPUTER IMPLEMENTATION

## 5.1 Introduction

This chapter describes the computer implementation of the developed models, along with their inputs and outputs as well as the graphical user interface (GUI) for each model. The end user interaction with the developed models is described as well.

Figure 5-1 depicts an overview of Chapter 5.

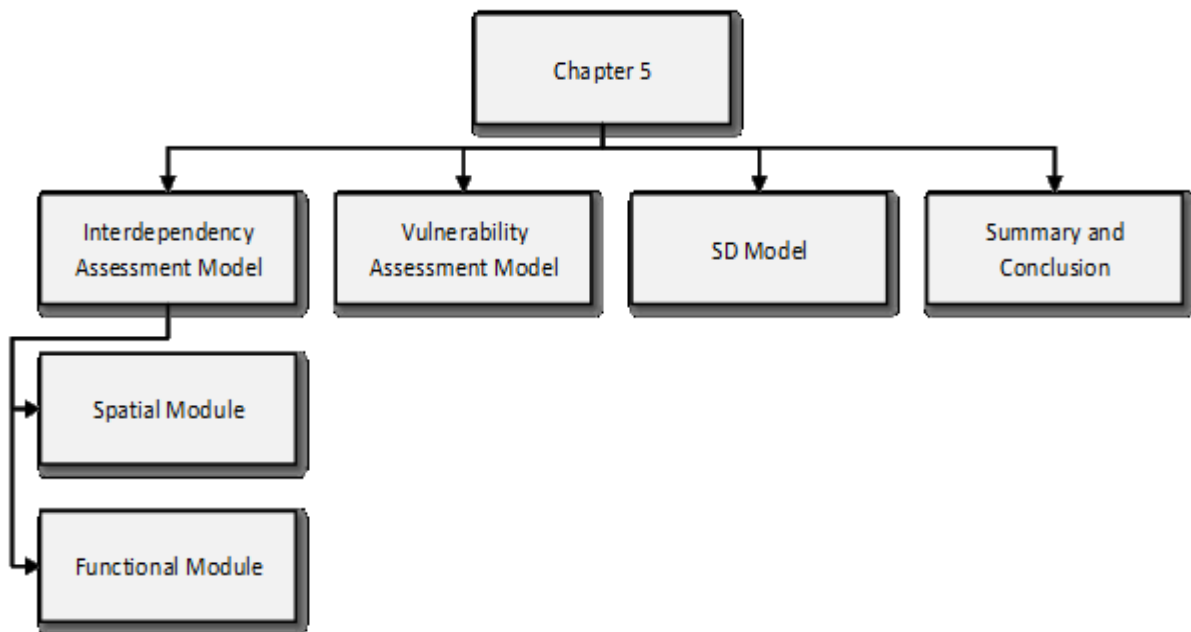


Figure 5-1 Chapter 5 overview

## 5.2 Interdependency Assessment Model

As mentioned in Chapter 4, the interdependency assessment model consists of: 1) spatial module, and 2) functional module. These two modules were implemented using python programming language and were embedded inside the ArcGIS environment. These modules were embedded inside the ArcGIS environment to;

facilitate importing of required inputs from the ArcGIS geodatabase and 2) facilitate exporting of their outputs into the ArcGIS geodatabase. The interactions between the end user and the two developed modules is shown in Figure 5-2.

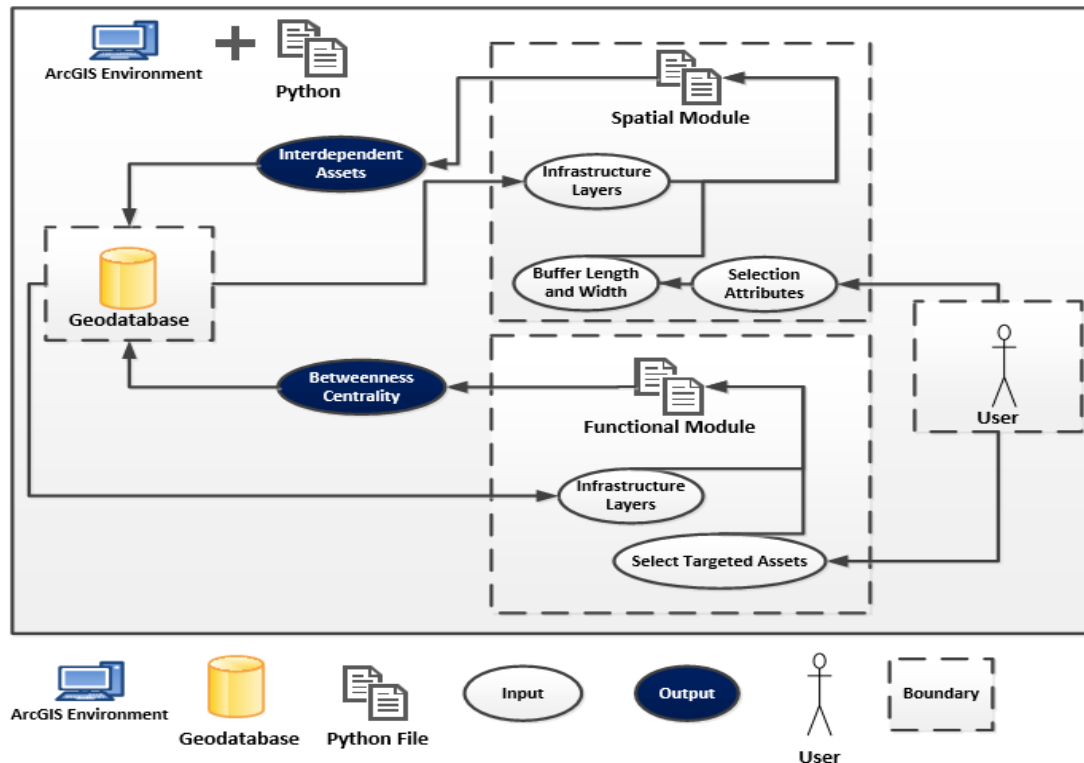


Figure 5-2 Interactions between the end user and the two implemented modules

### 5.2.1 Spatial Module

The spatial module has three inputs; geodatabases of infrastructure networks, buffer length and buffer width. The output of this module is in the form of bundles of spatially interdependent assets. These bundles are exported in two formats; new ArcGIS layers and new geodatabase table to host factors needed for vulnerability analysis of interdependent assets. The developed algorithm for this module was shown in Figure 4-

2. The user interface for this module is shown in Figures (5-4, 5-5, 5-6 and 5-7). In this module, the user performs the following operations:

- 1- The user starts by double clicking on the developed spatial module from the available ArcGIS toolboxes as shown in Figure 5-3.
- 2- The user form shown in Figure 5-4 will pop up. For example, the user starts by selecting the files of road and water networks for performing the spatial analysis. By double clicking on the road network icon, blue oval, shown in Figure 5-4, another user form will pop up to select the road network from the disk drive as shown in Figure 5-5. After selecting the road network's file, the network is imported into the module and then the user repeats the same steps for the water network. As mentioned in Chapter 4, the module is flexible enough to allow the user to import; 1) specific zones from targeted networks or 2) assets with specific attributes from targeted networks or 3) the entire infrastructure network.
- 3- The user then selects the buffer's length and width around each asset type. As mentioned in Chapter 4, a buffer is dynamic or static geometric boundary around the selected asset and it encapsulates the study zone. If there is another asset falling within that boundary, it will be interdependent with that asset.
- 4- The module then utilizes intersection and union operations of ArcGIS to overlay the selected networks and encapsulate the interdependent assets in a new layer as shown in Figure 5-6.



- 5- The new geodatabase table of interdependent assets is exported into the ArcGIS geodatabase. This new geodatabase table will include factors needed for assessing vulnerability of interdependent assets. Figure 5-7 shows the developed entity relationship diagram for the new geodatabase table for water, sewer and road assets. The entities, their attributes and relationships were discussed in Chapter 4.

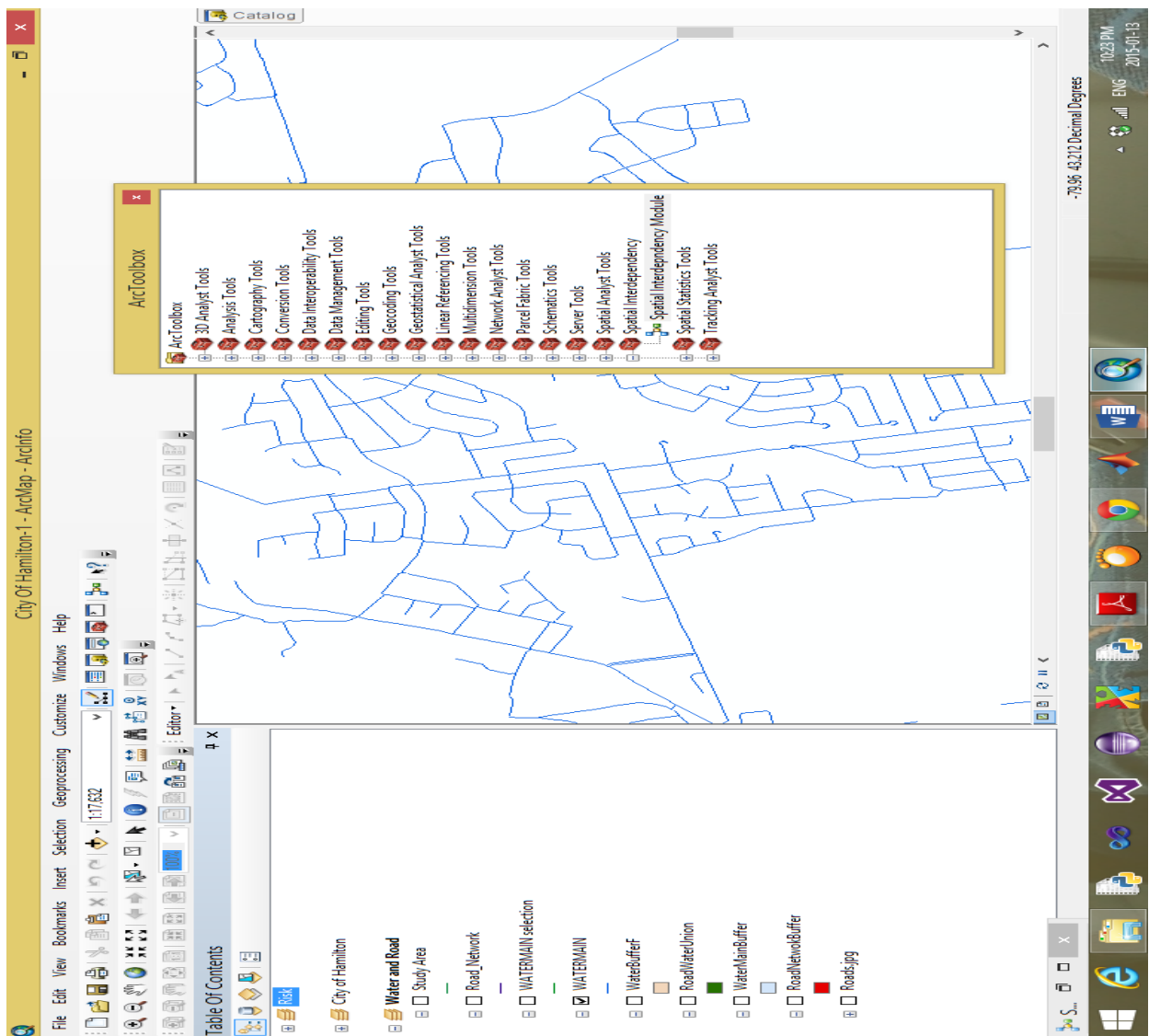


Figure 5-3 Spatial module and ArcGIS toolboxes

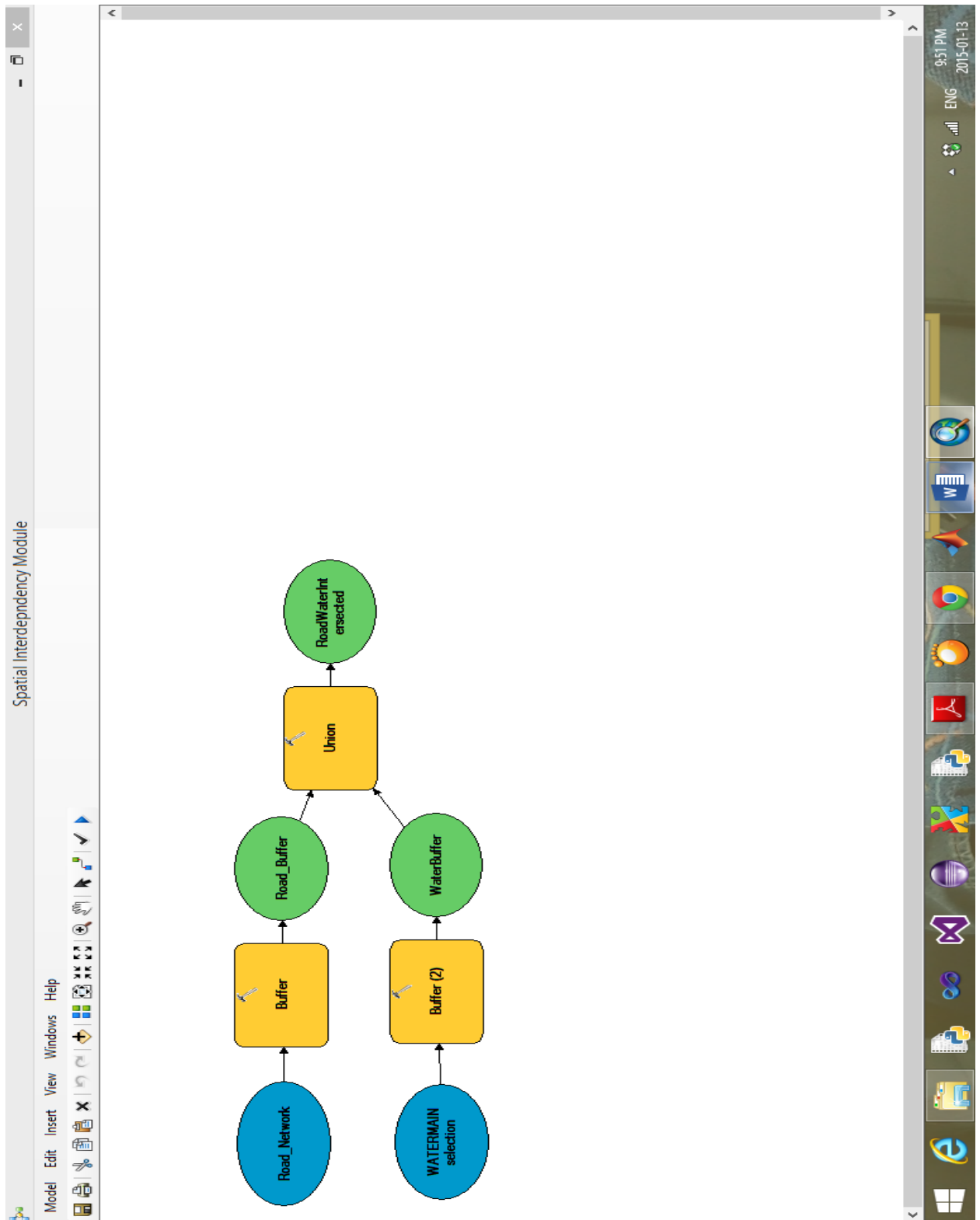


Figure 5-4 Spatial module user interface

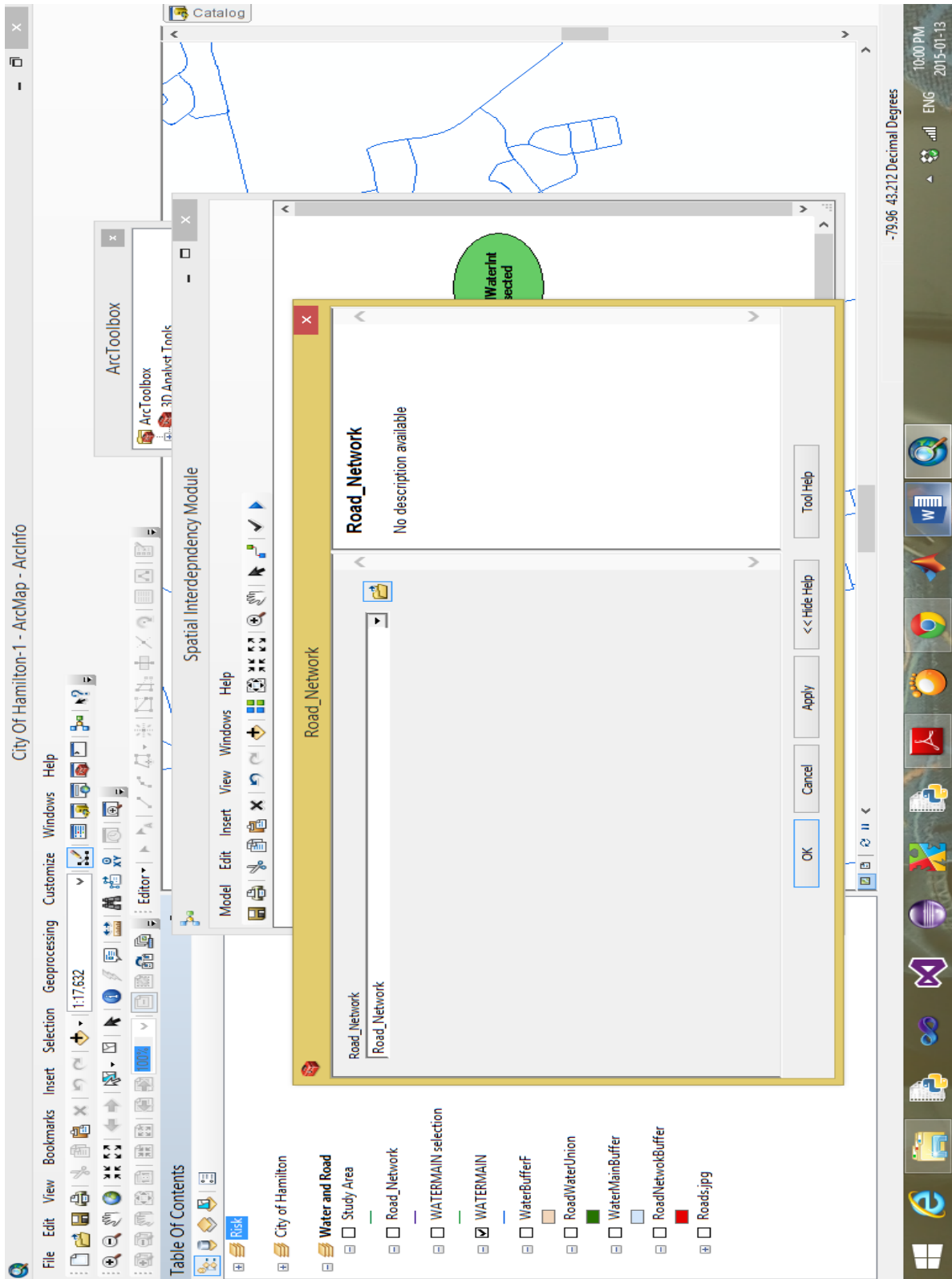


Figure 5-5 Selecting the road network

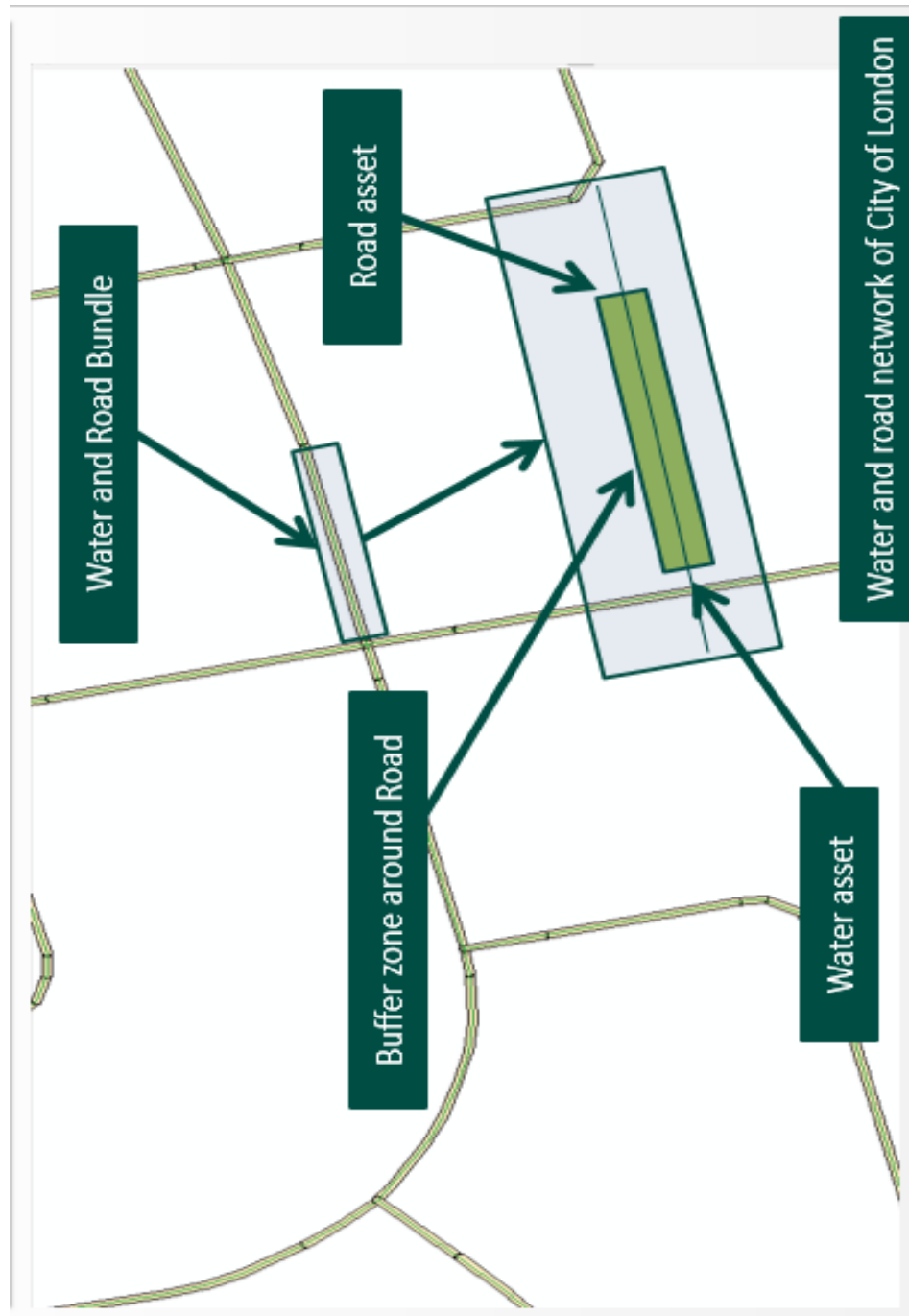


Figure 5-6 Spatial module output

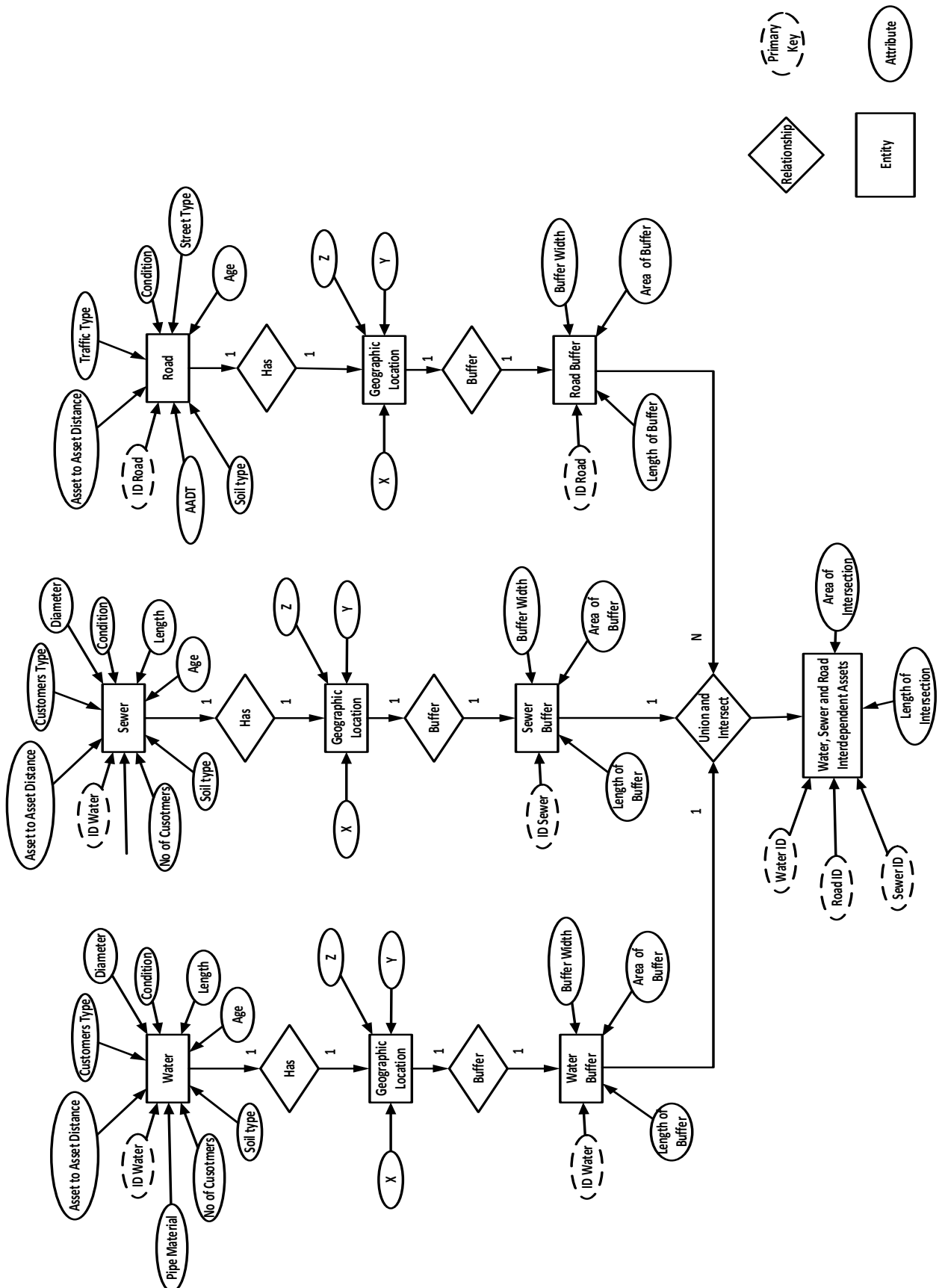


Figure 5-7 Implemented entity diagram for interdependent water, sewer and road

assets

### **5.2.2 Functional Module**

This module was embedded inside the ArcGIS environment and written using python programming language. The module utilizes an open source python library called “igraph” that has a collection of network analysis functions suitable for performing the operations described in the developed algorithm shown in Figure 4-5. The input for this module is the geometric layout of each infrastructure network. The output of this module is the calculated betweenness centrality for each asset in the infrastructure network. The user performs the following operations:

- 1- The user starts by importing the geometric layout of each infrastructure network from ArcGIS format (mxd) to a format called, GML, geography markup language format as shown in Figure 5-8. The geography markup language format (GML) is the XML grammar defined by the open geospatial consortium (OGC) to express geographical features. GML serves as a modeling language for geographic systems as well as an open interchange format for geographic maps; vector maps or raster maps.
- 2- After converting the geometric layout from mxd format to GML format, the algorithm starts by building up the edges and vertices lists needed for calculating the betweenness centrality. As mentioned in Chapter 4, assets are represented throughout vertices and edges represent the flow between any two vertices in the network. In this module, the user can find the betweenness centrality for; 1) a single asset or 2) a sample of the network or 3) the entire network.

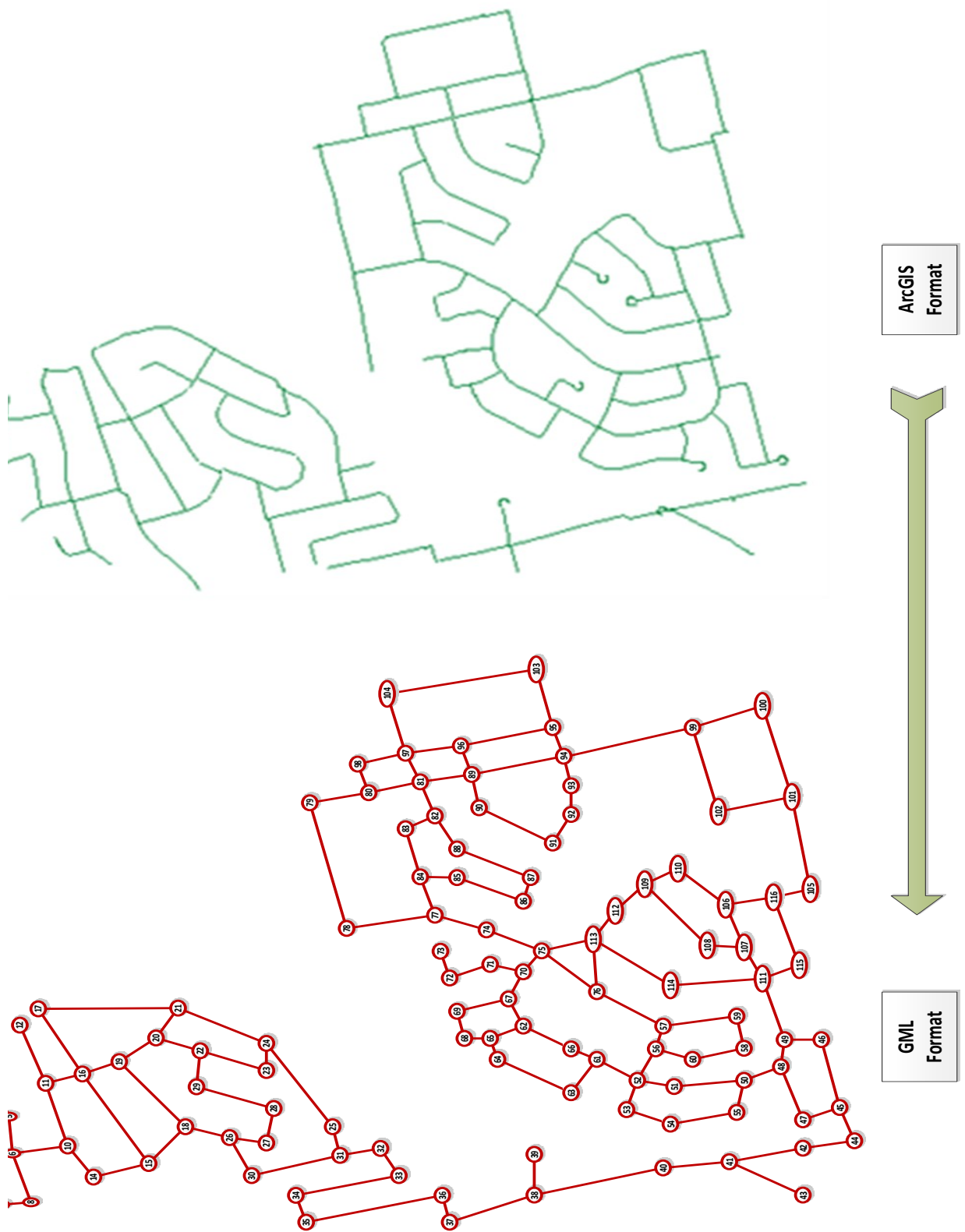


Figure 5-8 Converting ArcGIS map from mxd format to GML format

- 3- The calculated betweenness centrality for each asset can be exported into the ArcGIS geodatabase or to a new excel sheet. The excel output of this module is shown in Figure 5-9.

Vulnerability Model- Output - Excel													
FILE HOME INSERT PAGE LAYOUT FORMULAS DATA REVIEW VIEW LOAD TEST POWERPIVOT TEAM													
Clipboard Font Alignment Number Formatting Styles Editing													
A1 ID													
A B C D E F G H I J K L M N													
1	ID	Degree	Betweenness Centrality	Normalized Betweenness Centrality	Relative Betweenness Centrality								
2	1	1	0	0	0								
3	2	2	34	0.005278683	0.034892501								
4	4	3	98	0.015215029	0.09996032								
5	13	1	0	0	0								
6	5	2	124	0.019251669	0.126525591								
7	6	4	258	0.040055892	0.26525486								
8	7	2	34	0.005278683	0.034892501								
9	3	1	0	0	0								
10	8	2	34	0.005278683	0.034892501								
11	9	1	0	0	0								
12	10	3	252	0.03912436	0.257132653								
13	11	3	133	0.020648968	0.1357089								
14	14	2	143	0.02201522	0.145912577								
15	12	1	0	0	0								
16	16	4	146	0.022667288	0.14897368								
17	15	3	168.8333333	0.02621286	0.172727075								
18	17	2	62.66666667	0.009729338	0.063943041								
19	21	3	73	0.011333644	0.0748684								
20	19	3	69.66666667	0.010816126	0.071085615								
21	18	3	194.8333333	0.030248926	0.198001635								
22	20	3	40.83333333	0.006339595	0.041656013								
23	26	3	192.1666667	0.029834912	0.196080654								
24	27	1	0	0	0								
25	30	2	159	0.024685608	0.16223846								
26	22	2	12.33333333	0.001914817	0.012584535								
27	23	2	10.5	0.001630182	0.010713861								
28	24	3	82.5	0.01280857	0.084180333								
29	31	3	207.8333333	0.03267246	0.212066415								
30	32	2	174	0.027014439	0.177543975								
Functional Vulnerability-Mod Spatial Utility functions Functional Utility Functions Functional Analysis 2 AHP and MAUT Journal													

Figure 5-9 Functional module output



### 5.3 Vulnerability Model

The vulnerability model consists of three developed models to rate vulnerability of interdependent assets; 1) MAUT, 2) ANN and 3) FNN. These models were implemented outside the ArcGIS environment. The first model was implemented inside the excel environment and automated using VBA. The other two models were implemented using MATLAB programming language. At first, the three developed models were tested to determine the most suitable model based on the available datasets. After determining the most suitable model, it will be embedded in the SD model to decrease the computational time needed for identifying possible least cost intervention policies for vulnerable assets. The vulnerability model utilizes the ten factors identified in Chapter 3 to rate vulnerability of interdependent assets. The interactions between the end user and the three implemented models are shown in Figure 5-10. For the MAUT model, the user performs the following operations:

- 1- The user starts by importing bundles of interdependent assets from the ArcGIS geodatabase to the MAUT model. The user starts by selecting the location of the ArcGIS geodatabase from the disk drive and then the bundles are automatically imported into the excel sheet.
- 2- The user needs to define the utility functions for rating vulnerability of interdependent assets as shown in Figure 5-11. As shown in Figure 5-11, the user can use the default utility functions suggested from the surveys discussed in Chapter 4 or can define these functions.

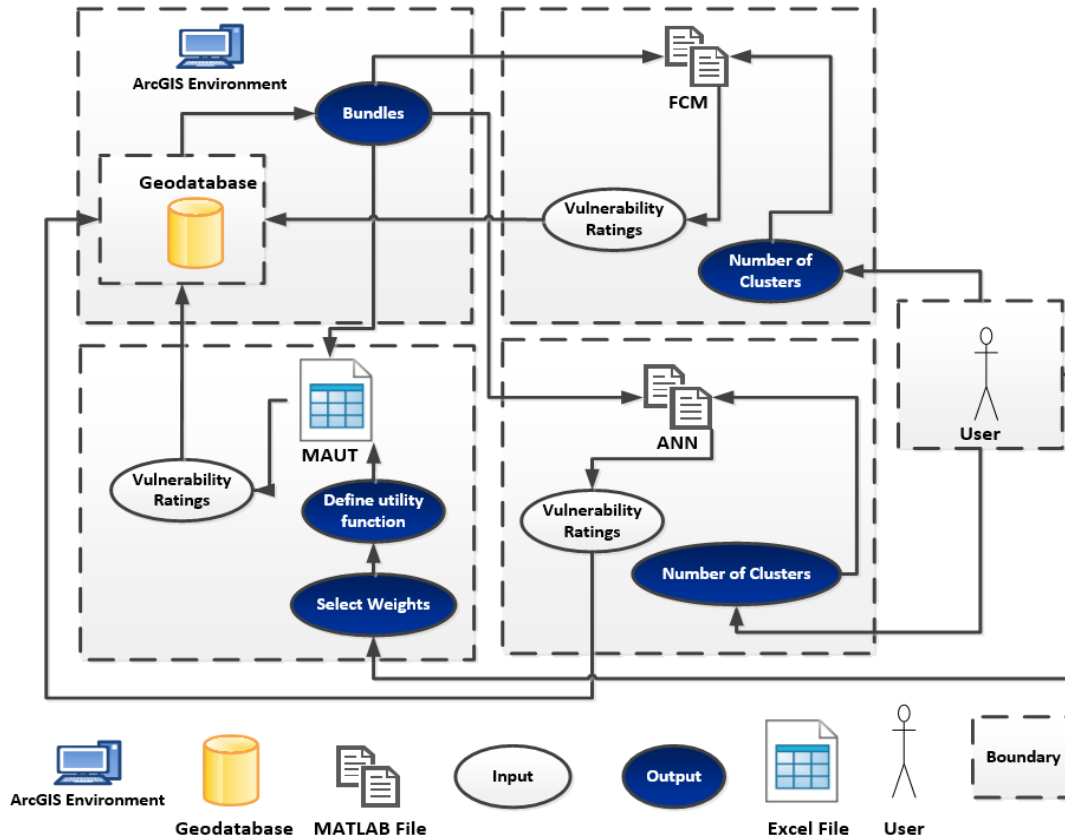


Figure 5-10 Interaction between the end user and vulnerability models

- 3- There are three ways to assign weights for the utility functions; 1) use the suggested weights elicited from the surveys or 2) the user defines these weights subjectively or 3) the user utilizes AHP technique integrated inside MAUT to assign these weights objectively as shown in Figure 5-12.
- 4- The MAUT model will calculate vulnerability ratings for interdependent assets as shown in Figure 5-13.
- 5- The results can be exported into the ArcGIS geodatabase for further analysis and visualization.



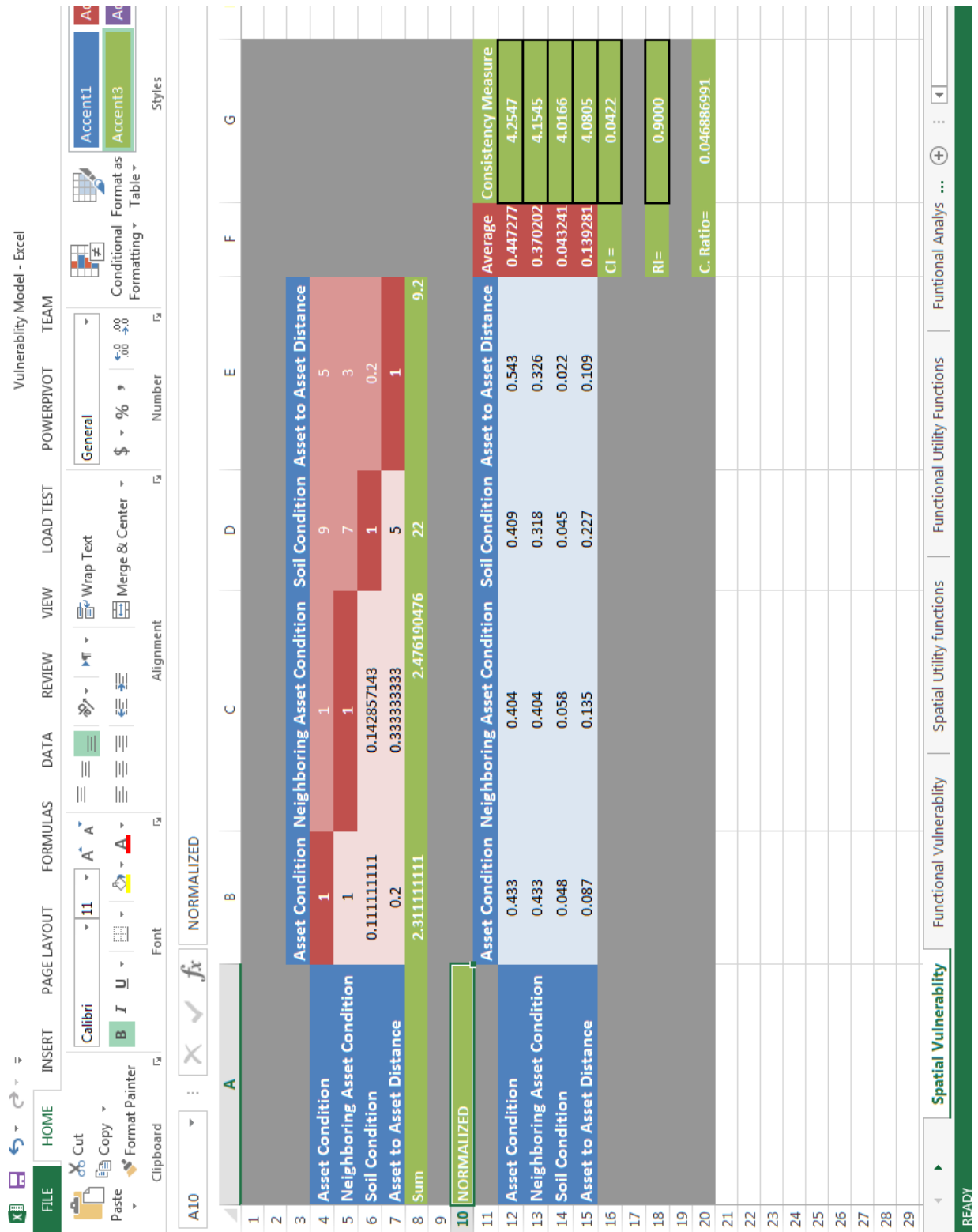


Figure 5-12 Assigning weights for the utility functions in MAUT

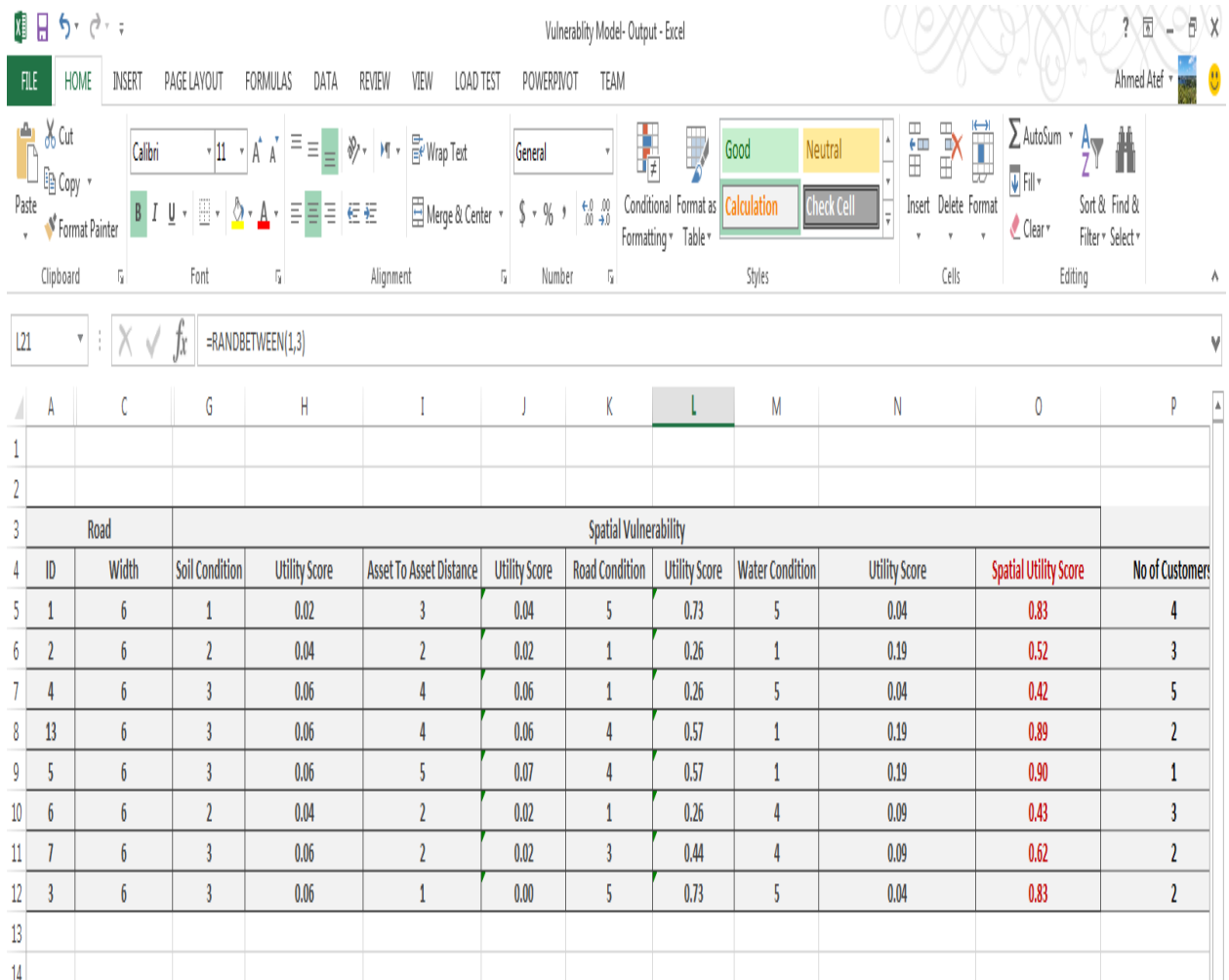


Figure 5-13 MAUT output

For the ANN model, it utilizes the developed self-organized maps algorithm shown in Figure 4-11. As shown in Figure 5-10, the user starts by defining the number of clusters, (i.e. vulnerability ratings). The user imports interdependent bundles from the ArcGIS geodatabase to MATLAB environment. The ANN model then performs the procedures described in Chapter 4 to cluster interdependent assets into the defined number of clusters. When the user is satisfied with the mean square error (MSE) for the ANN technique, vulnerability ratings are exported from MATLAB to the geodatabase of ArcGIS for further analysis and visualization.

The developed FCM algorithm shown in Figure 4-12 was implemented using MATLAB programming language. The user interaction with this model is similar to ANN. The user starts by defining the number of required clusters (i.e. vulnerability ratings) as shown in Figure 5-10. The user then imports the bundles of interdependent assets from the ArcGIS geodatabase to MATLAB environment. The implemented algorithm performs the six steps shown in Figure 4-12. When the user is satisfied with the mean square error for FCM, vulnerability ratings of interdependent assets are exported from MATLAB to the ArcGIS geodatabase for further analysis and visualization.

#### **5.4 System Dynamics Model**

The SD model was implemented using C#. The simulation engine for Anylogic 7 was embedded inside the system dynamic model using C# and was supplemented with the two developed optimization algorithms discussed in Chapter 4. The FCM model was also embedded inside the SD model to facilitate the calculations needed for rating vulnerability of interdependent assets at each time step of the simulation. The interactions between the end user and the developed model is shown in Figure 5-14. Table 5-1 provides a summary for the required SD variables with their sources and purposes. A sample from the GUI used to define SD variables related to the road assets is shown in Figure 5-15. As mentioned in Chapter 4, the SD is composed of two tiers; tier one for the bundle level is SD and dynamic programming and tier two for the network level is SD and genetic algorithm (GA). For the first tier, the needed inputs for the dynamic programming algorithm are shown in Table 5-2.

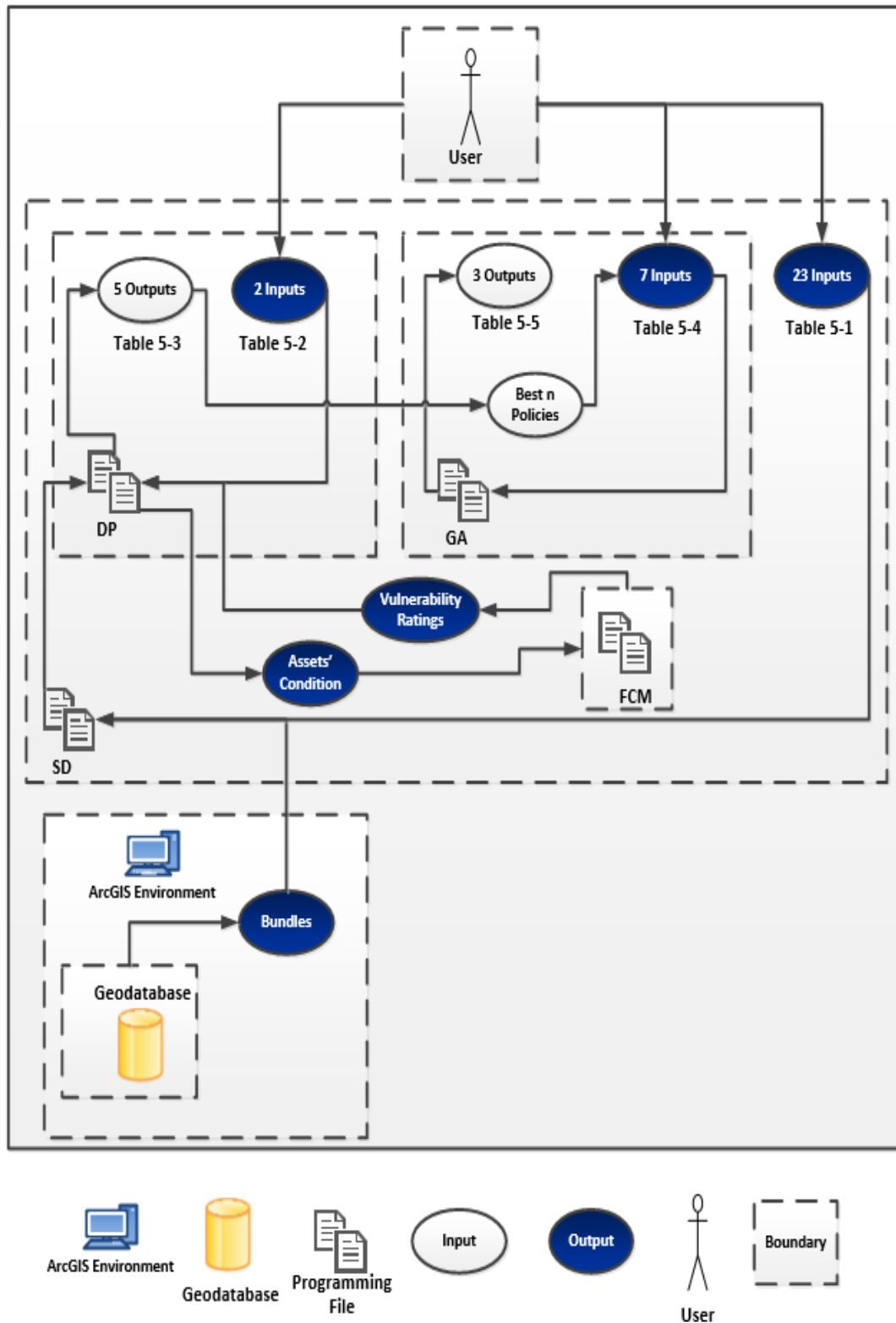


Figure 5-14 Interaction between the end user and the developed system dynamic model

The user starts by importing bundles of interdependent assets from the ArcGIS geodatabase into the SD program. The user then defines the inputs shown in Tables 5-1 and 5-2. The developed algorithm shown in Figure 4-24 is then utilized to find the outputs shown in Table 5-3. The main output of this tier is an intervention report that contains the best n policies at bundle level. In this intervention report, for each time step and for each asset in the bundle; the decision maker can find asset's condition, its LOS, its vulnerability, intervention action, intervention cost, total lifecycle cost and total satisfaction as shown in Table 5-3.

The GUI for road asset inputs is displayed within a window titled 'Road'. It features several input sections:

- Condition:** Target and Trigger input fields, both set to 3.
- LOS:** Target and Trigger input fields, both set to 3.
- Vulnerability:** Target and Trigger input fields, both set to 5.
- Other Costs:** Operating Cost input field.
- Transition Matrix =**: A 4x4 grid of input fields with values:
 

0.98	0.02	0.00	0.00
0.00	0.38	0.02	0.00
0.00	0.00	0.97	0.03
0.00	0.00	0.00	1.00
- Intervention Actions:**
  - Action: Minor, Cost: 125.00
  - Action: Major, Cost: 250.00
  - Action: Replace, Cost: 500.00
  - An 'Add Action' button is located to the right.
- Action Map:** A table with 3 columns and 3 rows:
 

	1	2	3
1	Action	Action	
2	1		
3			1

A Windows taskbar is visible at the bottom of the screen with icons for various applications including File Explorer, Edge, Word, PowerPoint, and the Start menu.

Figure 5-15 GUI for road asset inputs



A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T				
Scenario ID	Average Score	Total Cost	Year	Action	Condition	Vul Score	Cost This period	Year	Action	Condition Vul	Score	Cost This period	Year	Action	Condition Vul	Score	Cost This period	Year	Action				
1	80	43.85714286	56250	100	1	3.427874641	6	60	0	95	1	3.112834	6	60	0	90	1	2.766832	6				
2	144	43.85714286	322500	100	1	2.399908802	6	27	0	95	1	2.026666	6	27	0	90	1	1.663742	6				
3	145	43.85714286	322500	100	1	2.026666153	6	27	0	95	1	1.663742	6	27	0	90	1	1.322876	6				
4	263	43.85714286	56250	100	1	3.427874641	6	60	0	95	1	3.112834	6	60	0	90	1	2.766832	6				
5	79	44.47619048	56250	100	1	3.706591664	5	73	0	95	1	3.427875	6	60	0	90	1	3.112834	6				
6	81	44.47619048	56250	100	1	3.112834278	6	60	0	95	1	2.766832	6	60	0	90	1	2.399909	6				
7	198	44.47619048	56250	100	1	3.706591664	5	73	0	95	1	3.427875	6	60	0	90	1	3.112834	6				
8	309	44.47619048	56250	100	1	3.112834278	6	60	0	95	1	2.766832	6	60	0	90	1	2.399909	6				
9	147	44.52380952	322500	100	1	2.766863391	6	60	0	95	1	2.354232	6	27	0	90	2	2	6				
10	149	44.52380952	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	3.112834	6				
11	227	44.52380952	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	2.766832	6				
12	84	44.76190476	322500	100	2	1	6	53	18750	95	1	2.399909	6	27	0	90	1	2.026666	6				
13	12	45.0952381	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	2.766832	6				
14	55	45.0952381	322500	100	2	2	6	27	18750	95	1	2.766832	6	60	0	90	1	2.399909	6				
15	78	45.0952381	56250	100	1	3.947431898	5	73	0	95	1	3.706592	5	73	0	90	1	3.427875	6				
16	85	45.0952381	303750	100	1	2.766832057	6	60	0	95	1	2.399909	6	27	0	90	1	2.026666	6				
17	106	45.0952381	56250	100	1	3.947431898	5	73	0	95	1	3.706592	5	73	0	90	1	3.427875	6				
18	119	45.0952381	322500	100	1	2.399908802	6	27	0	95	1	2.026666	6	27	0	90	1	1.663742	6				
19	346	45.0952381	303750	100	1	2.766832057	6	60	0	95	1	2.399909	6	27	0	90	1	2.026666	6				
20	349	45.0952381	322500	100	1	2.399908802	6	27	0	95	1	2.026666	6	27	0	90	1	1.663742	6				
21	161	45.14285714	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	2.766832	6				
22	107	45.42857143	341250	100	1	1.663741567	6	27	0	95	1	1.322876	6	53	0	90	4	1	6				
23	44.52380952	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	2.766832	6	6				
24	44.52380952	322500	100	1	2.354231623	6	27	0	95	2	2	6	27	18750	90	1	2.766832	6	6				
Sheet1																			Best n Scenarios	+			100%

Figure 5-16 The SD and dynamic programming output

Table 5-1 Summary of SD model variables

Variables	Source	Purpose
Asset condition	ArcGIS Geodatabase	To model asset's performance at each time step of the SD model
Deterioration rate	Road (Sarja, 2006) - Water and Sewer (Osman, 2012)	
Intervention actions	(Hashemi et al, 2008)	To improve asset's performance
Intervention actions cost	(Hashemi et al, 2008)	To calculate the intervention action's cost at each time step of the SD
Vulnerability rating	FCM model	To rationale intervention polices based on asset's vulnerability.
Level of service (LOS)	Assumed (correlated with condition- i.e. linear, exponential...etc.)	To rationale intervention polices based on asset's LOS.
Target condition	decision maker (assumed)	To evaluate each intervention policy feasibility at bundle level
Trigger condition	decision maker (assumed)	
Target LOS	decision maker (assumed)	
Trigger LOS	decision maker (assumed)	
Target vulnerability	decision maker (assumed)	
Trigger vulnerability	decision maker (assumed)	
Satisfaction from LOS	Decision maker (assumed)- discussed with the experts	To measure the decision maker's satisfaction asset's LOS
Satisfaction from condition	Decision maker (assumed)- discussed with the experts	To measure the decision maker's satisfaction due to asset's condition
Satisfaction from vulnerability	Decision maker (assumed)- discussed with the experts	To measure the decision maker's satisfaction due to asset's vulnerability
Total satisfaction	Decision maker (assumed)- discussed with the experts	To rationale intervention polices based on asset's condition, its LOS and its vulnerability.
Weight of satisfaction from condition	Decision maker (assumed)- discussed with the experts	To decide the importance of improving decision maker's satisfaction from asset's condition, its LOS and its vulnerability

Weight of satisfaction from LOS	Decision maker (assumed)- discussed with the experts	
Weight of satisfaction from vulnerability	Decision maker (assumed)- discussed with the experts	
Improvement in LOS	Assumed (correlated with condition- i.e. linear, exponential...etc.)	If an action is applied, then the ratings of LOS, condition and vulnerability will improve as well.
Improvement in condition	decision maker (assumed)	
Improvement in vulnerability	FCM model	
Lifecycle costs	(Hashemi et al, 2008)	To identify possible least cost intervention policies
Interest rate	Statistics Canada 2013	To consider the value of money at each time step

Table 5-2 Dynamic programming algorithm inputs

Inputs	Source	Purpose
n	decision maker (assumed)	To determine the best n policies required by the decision maker
Simulation interval time	decision maker (assumed)	To determine the analysis period of the SD and dynamic programming

Table 5-3 SD and dynamic programming algorithm outputs

Outputs	Each policy report contains	Intervention report contents
The best n policies at bundle level	For each time step and for each asset in the bundle	Asset condition, LOS and vulnerability
		Intervention action at each time step
		Intervention cost at each time step
		Total lifecycle cost
		Total satisfaction at each time step

For the second tier, the SD model is supplemented with GA to find a near optimal policy considering the ranked policies identified by the dynamic programming algorithm. The required inputs for GA algorithm are shown in Table 5-4. The GUI used for defining these inputs is shown in Figure 5-17. The expected outputs for this tier are shown in Table 5-5.

Table 5-4 GA inputs

Inputs	Source	Purpose
Population size	decision maker (assumed)	To determine the SOGA population size
Mutation rate	decision maker (assumed)	To prevent local minimum or maximum
Crossover rate	decision maker (assumed)	To prevent local minimum or maximum
No of trials	decision maker (assumed)	To determine the allowable number of trials for SOGA
Available budget	decision maker (assumed)	To select the optimum intervention policies at network level
n	SD and dynamic programming	To seed the initial population of the SOGA
m	decision maker (assumed)	To determine the best m solutions at the network level required by the decision maker

Table 5-5 SD and GA outputs

Output	Intervention report contents
The best m solutions at network level	The best policy for each bundle
	The total cost for that solution
	Total satisfaction for each solution
Time to reach the optimum solution	
The best solution cost	

File
Assets

Single Asset

Two Assets Bundle

Three Assets Bundle

Frequency: 5 Years

Time Horizon: Years

Modify

Dynamic Programming Optimization

Starting Bundle: 1

Ending Bundle: 50

Project Level

Optimization Parameters

Objective	Weight
Objective 1:	
Objective 1:	
Objective 1:	

File Location: C:\Data\3bundle\_list.xlsx

Starting Bundle: 1

Ending Bundle: 50

Run

Genetic Algorithm Optimization

Optimization Parameters

Population Size:

Crossover Rate:

Mutation Rate:

Number of Trials:

0 / 0

Figure 5-17 GUI for the inputs of the two proposed supplemented algorithms

## 5.5 Summary and Conclusion

This chapter described the computer implementation of the developed models, along with their inputs and outputs as well as the graphical user interface (GUI) for each model. The end user interaction with the developed models was described as well. The interdependency assessment model were implemented using python programming language and were embedded inside the ArcGIS environment. The vulnerability model consists of three developed models to rate vulnerability of interdependent assets; 1) MAUT, 2) ANN and 3) FNN. These models were implemented outside the ArcGIS environment. The first model was implemented inside the excel environment and automated using VBA. The other two models were implemented using MATLAB programming language. After determining the most suitable model as will be shown in next chapter, it will be embedded in the SD model to decrease the computational time needed for identifying possible least cost intervention policies for vulnerable assets. The SD model was implemented using C#. The simulation engine for Anylogic 7 was embedded inside the system dynamic model using C# and was supplemented with the two developed optimization algorithms discussed in Chapter 4.

# Chapter 6 : CASE STUDIES

## 6.1 Introduction

Two case studies are analyzed and used to demonstrate the application of the developed research framework as shown in Figure 6-1. The two case studies were obtained from the Cities of London and Hamilton, Ontario. The sources used for defining the inputs of the SD model were discussed in Chapters 4 and 5. The analysis discussed in the following subsections was performed on AMD Quad-core processor 1.9 GHZ with random access memory of 8 GB and cash memory of 4MB.

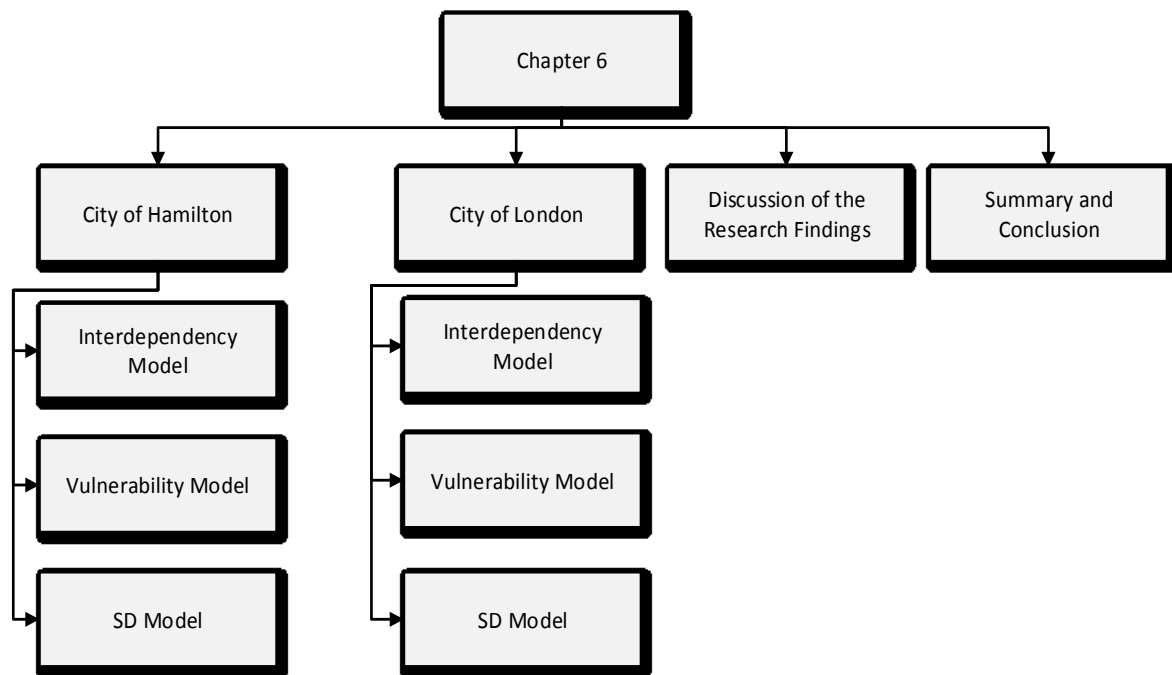


Figure 6-1 Chapter overview

## 6.2 City of Hamilton

The data analysed in this section is for the City of Hamilton water distribution and road networks. As mentioned in Chapter 3, the City of Hamilton owns 1,950 km of

water assets with replacement value of CAD 1.82 billion and 3,000 km of road assets with replacement value of CAD 3.25 billion (SOI Report, 2005). The collected datasets consists of 43,031 datasets for the water network and 12,350 for the road network.

### **6.2.1 Interdependency Assessment Model**

After removing incomplete records, 10,650 datasets for water network and 6000 datasets for road network were considered for the interdependency assessment model. The interdependency model consists of; 1) spatial module and 2) functional module. The developed spatial module shown in Figure 4-2 was implemented using python and was embedded inside the ArcGIS environment as a new geoprocessing tool. In this case study, the analysis started by defining the targeted layers for spatial interdependency analysis (i.e. water and road networks). Subsequently, the parameters for buffering construction around water and road assets were initialized. The bundle's length was 200m and its width was the same as the street segment's width. Interdependent water and road assets are grouped into a new layer called interdependent water and road assets layer. The number of bundles constructed by this module was 12,350 bundles. For the new interdependent layer of water and road assets, a new geodatabase file was generated to include data required for the vulnerability assessment model. The computational time for this module was 45.2 sec.

As mentioned in chapter 4, the developed functional module is utilized to calculate the relative betweenness centrality (RBC) and use it as a metric for judging the likely influence of an asset failure on its neighboring assets' performance. Figure 6-2 shows a sample from the road network considered in this case study with the ID of each asset.



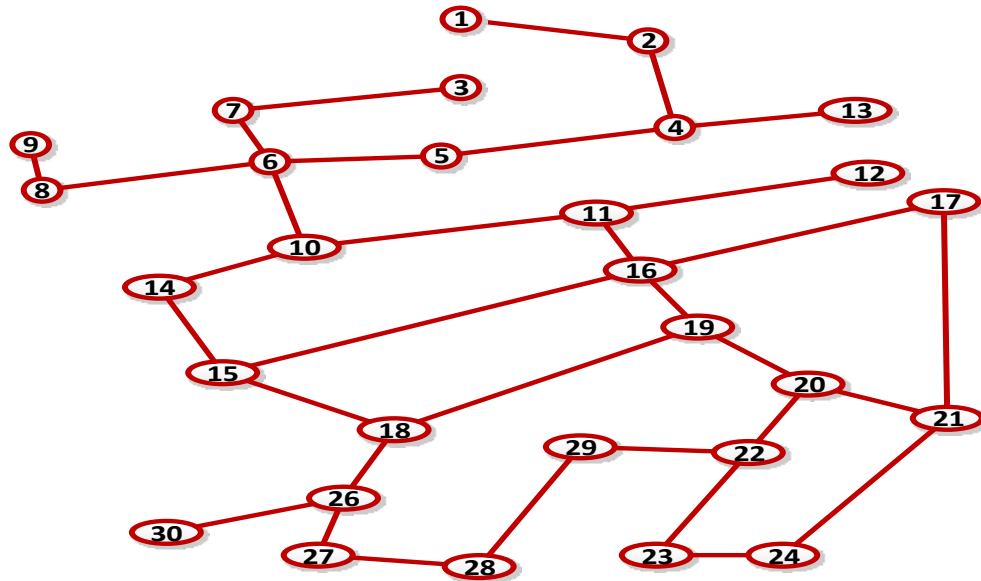
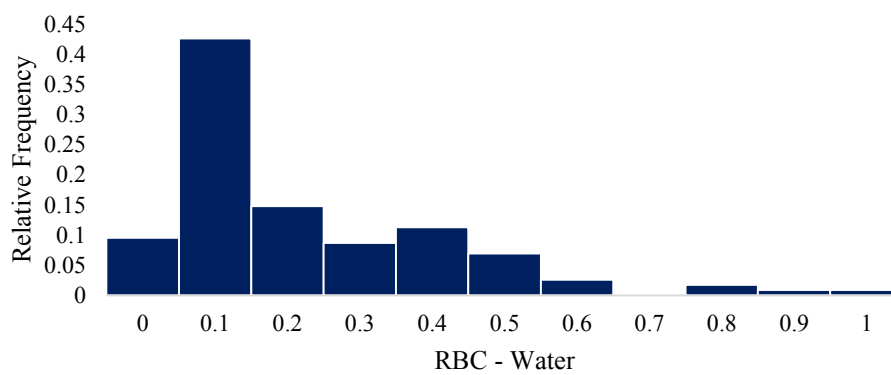


Figure 6-2 A sample from the road network with asset's ID

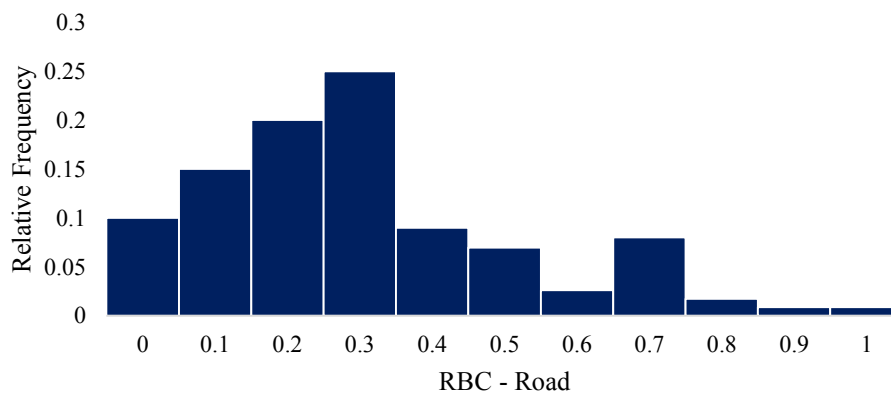
The developed functional module shown in Figure 4-5 was implemented using python and embedded inside ArcGIS. The module starts by importing the targeted network of each asset type. The module then starts building vertices and edges lists needed for applying the algorithm of the function module. After performing the functional module analysis, RBC is imported back into ArcGIS geodatabase of the analyzed assets as shown in Table 6-1. The computational time was 10.5 min. For the road network sample shown in Figure 6-2, assets with ID (1, 2, and 13) are located at the end of the road network so they do not control the flow inside the network and therefore their RBC score is zero or close to zero. On the other hand, asset (6) has RBC score of one meaning that this asset is vital to network's functionality. Figure 6-3 shows a comparison between RBC histograms for both assets. The water network is more skewed to the right indicating lower degree of connectivity compared to the road network.

Table 6-1 RBC for a sample from the road network, Hamilton

Asset ID	Relative betweenness centrality (RBC)
1	0.00
2	0.13
13	0.00
4	0.3
5	0.48
6	1.00
7	0.13



a) Water Network



b) Road Network

Figure 6-3 RBC for water and road networks, Hamilton

### 6.2.2 Vulnerability Model

The vulnerability model consists of three developed models; 1) MAUT, 2) ANN and 3) FCM. These three models were utilized to analyze the 12,350 bundles of interdependent water and road assets. The outputs of MAUT model for these bundles are shown in Figure 6-4. As mentioned in Chapter 4, vulnerability is measured on a scale from 1 to 10 where 1 is very low vulnerability and 10 is very high vulnerability. This scale can be customized by the decision maker to suit his or her preferences as discussed in Chapter 5.

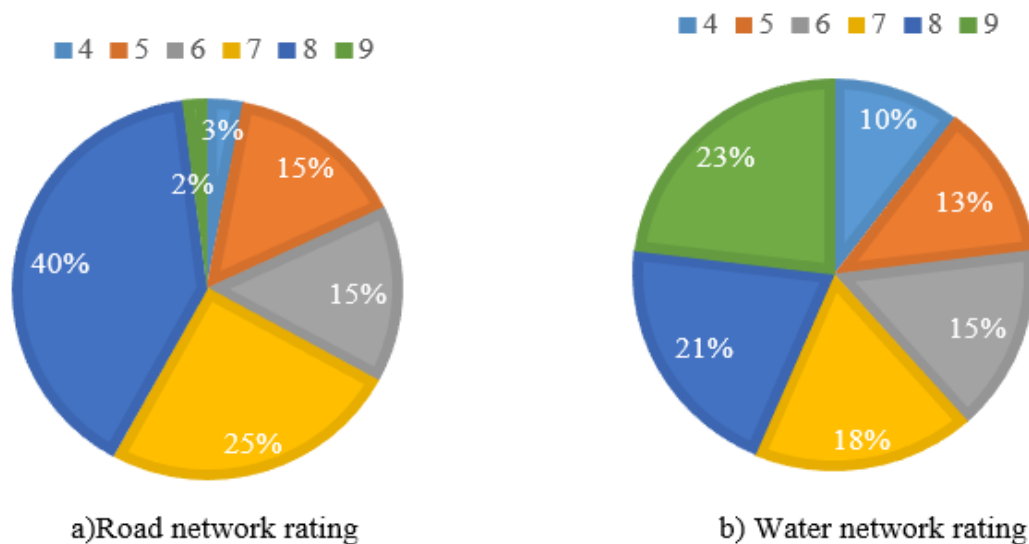


Figure 6-4 Vulnerability rating for City of Hamilton using the MAUT model

Table 6-2 shows a comparison between the outputs obtained using MAUT and the other two models. For the water network, the MSE model was 5.29 for the FCM model and 11.22 for the ANN model. For the road network, the MSE model was 11.5 for the FCM model and 7.21 for the ANN model. Figure 6-5 shows the results of the FCM model when being visualized inside ArcGIS environment.

Table 6-2 Comparison between the three computational techniques for the City of Hamilton

Network	Percentages of assets in each vulnerability rating (%)										
	Model	1	2	3	4	5	6	7	8	9	10
Water	MAUT	0	0	0	2	20	22	25	30	1	0
	ANN	0	0	0	4	15	18	32	26	5	0
	FCM	0	0	1	1	22	20	24	27	3	2
Road	MAUT	0	0	0	3	15	15	25	40	2	0
	ANN	0	0	3	4	10	20	18	44	1	0
	FCM	0	0	4	5	14	14	22	36	4	1

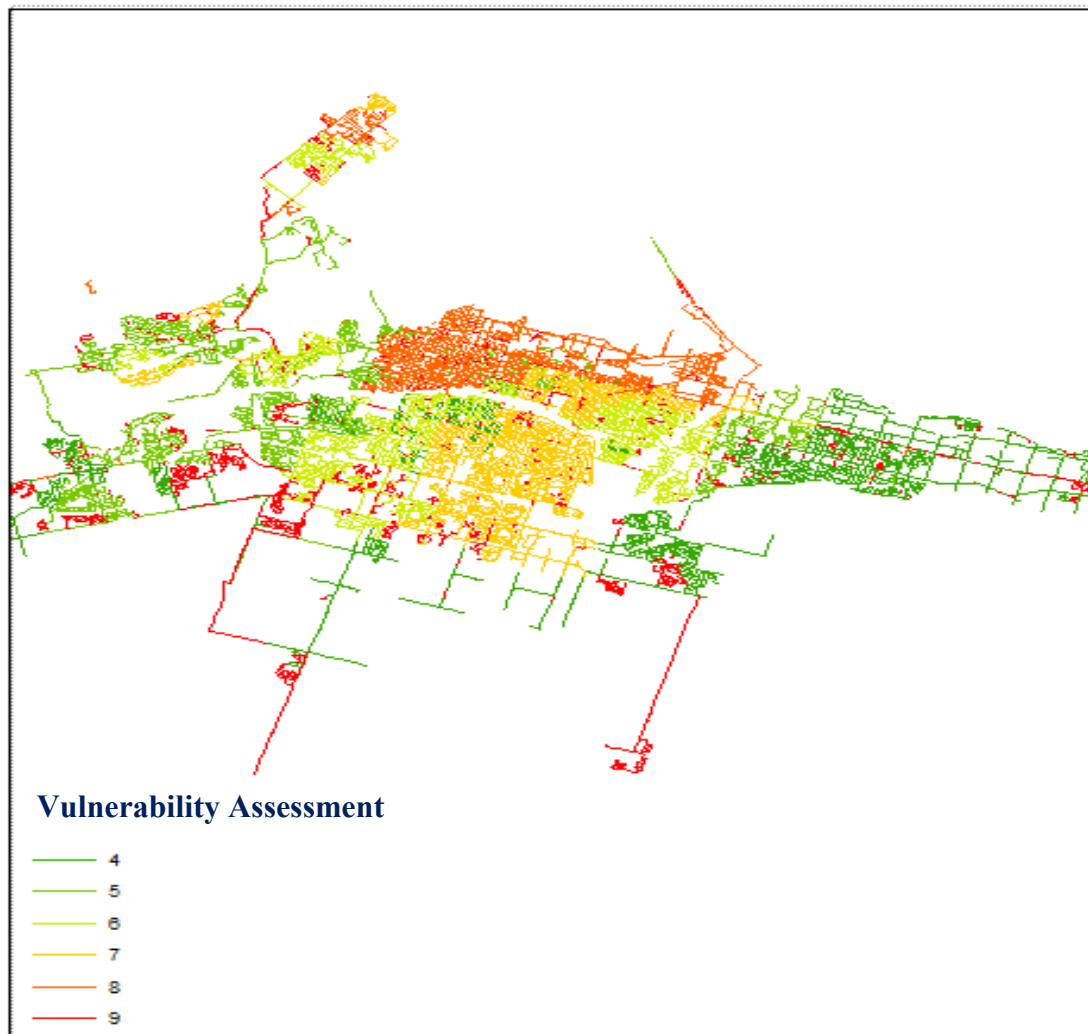


Figure 6-5 Vulnerability assessment using the FCM model

Based on such results, the FCM model had an average MSE of 6.25 for both assets and the ANN model had an average MSE of 11.22. The FCM model showed better performance than the ANN model in mimicking experts' judgement.

### 6.2.3 System Dynamics Model

First, the casual loops R1 and R2 of the SD model were verified by using two examples from the literature; one for road assets (Sarja, 2006) and one for water assets (Osman et al, 2012). The SD model was tested to see if it can replicate results generated by Sarja (2006) and Osman et al, (2012). The model was tested also to measure its sensitivity under three conditions; 1) no intervention action is applied, 2) intervention actions are applied based on thresholds for asset's condition or its LOS or its vulnerability and 3) imposing intervention action on close time intervals. The first two conditions were described in Chapter 4 (Figures 4-15 and 4-18). For the third condition, Figure 6-6 shows an example for a deterioration curve generated by the SD model for a water asset with intervention actions being applied once the asset moves from condition state 5 to 4. The SD was capable of replicating results of Sarja (2006) and Osman et al, (2012) and it was capable of handling extreme inputs as shown in Figure 6-6.

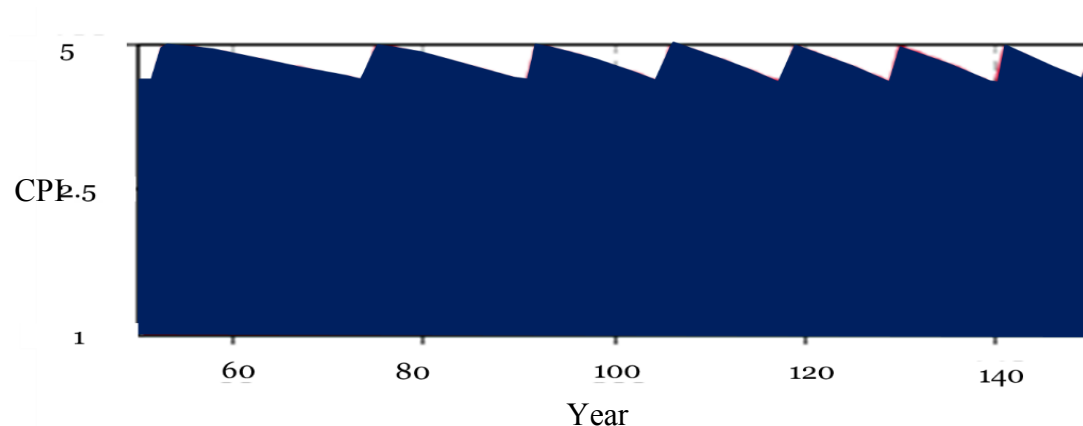


Figure 6-6 Water asset deterioration curve

The SD model was then applied on the bundle level and the network level. Results of this analysis were discussed with the experts and their feedback is included in the section of discussion of the research findings. For the bundle level, Table 6-3 shows the top ten scenarios for bundle number 1 which consists of water asset and road asset.

Table 6-3 Top ten scenarios for bundle number 1

Policy	Water	Cost CAD	Road	Cost CAD
	Average satisfaction/year (%/year)		Average satisfaction/year (%/year)	
1	76.1	686250	73.2	343125
2	77.2	776500	76	388250
3	78	908850	79.1	454425
4	80.1	1046250	82.1	523125
5	82	1083750	82	541875
6	82.1	1158750	83.6	579375
7	86.1	1196250	84.1	598125
8	88.1	1258750	87.7	629375
9	90.1	1458750	89.1	729375
10	92.1	1504400	90.1	752200

The analysis period for these two assets was 30 years. The total number of scenarios evaluated for this bundle using dynamic programming algorithm was 90,000 and these policies were ranked based on Equation 4-15. The computational time was 1.1 sec. The variance in average satisfaction of the decision maker for the water asset between policy 1 and 10 is 21.02 % with cost variance of 119.2 %. This means in order to improve the average satisfaction by 21.02 %, investments need to be increased by 119.2% for this water asset.

Samples ranging between 100 to 12,350 bundles were selected to be optimized at the network level. These samples were used to test the performance of traditional GA

against the modified GA shown in Figure 6-7. The population size was 10000, mutation rate was 0.4, crossover rate was 0.6 and number of trials was 1000. For 100 bundles, the available budget for water assets was CAD 160,000,000 and CAD 70,000,000 for road assets. For traditional GA, the allocated budget for water assets was CAD 179,490,000 and 98,719,500 CAD for road assets. For the modified GA algorithm, the allocated budget for water assets was CAD 150,200,000 and 88,312,200 CAD for road assets. These results were obtained using the equations articulated in the GA section in Chapter 4 (Equations 4-12, 4-13, 4-14 and 4-17). By closely examining the results, the modified GA showed slower growth rate in the computational time needed for optimizing intervention policies at network level. For the 12,350 bundles, the computational time for the modified GA was 51.40 % less than traditional GA.

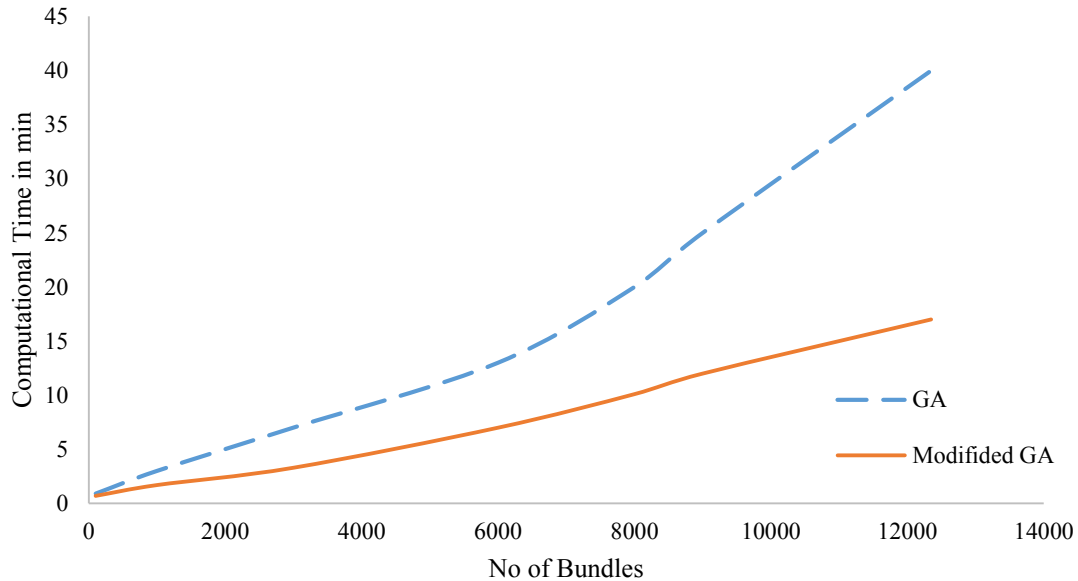


Figure 6-7 Comparison between traditional GA and modified GA

A sample for the best solutions obtained at the network level using the modified GA is shown in Table 6-4. The best solution and its policies are shown in Figure 6-8. The assigned budget for the best solution was 543 M for 12,350 bundles. Solution 6 assigns better intervention policies for each bundle however the assigned budget exceeds the available budget (550 M) by 137 M. Appendix C has more details about the intervention actions taken within each policy.

Table 6-4 Sample for the best solutions obtained at the network level from the modified GA algorithm

Bundle ID	1	47	238	4590	6790	11250	Budget
Solution 1	Policy 10	Policy 7	Policy 6	Policy 4	Policy 7	Policy 9	543 M
Solution 2	Policy 7	Policy 4	Policy 4	Policy 2	Policy 8	Policy 6	589 M
Solution 3	Policy 6	Policy 2	Policy 5	Policy 1	Policy 4	Policy 4	605 M
Solution 4	Policy 4	Policy 5	Policy 3	Policy 2	Policy 6	Policy 3	625 M
Solution 5	Policy 7	Policy 3	Policy 1	Policy 3	Policy 4	Policy 2	656 M
Solution 6	Policy 5	Policy 2	Policy 2	Policy 1	Policy 2	Policy 2	687 M

### 6.3 City of London

The city of London according to the 2013 SOI report owns; 1) water network of 1,570 km with total replacement value of \$2.7 billion, 2) sewer network of 1,430 km with replacement value of 2 billion and 3) road network of 3,717 km with replacement cost of 1.8 billion. The collected datasets consists of 9145 datasets for road network, 44973 for sewer network and 24567 for water network.



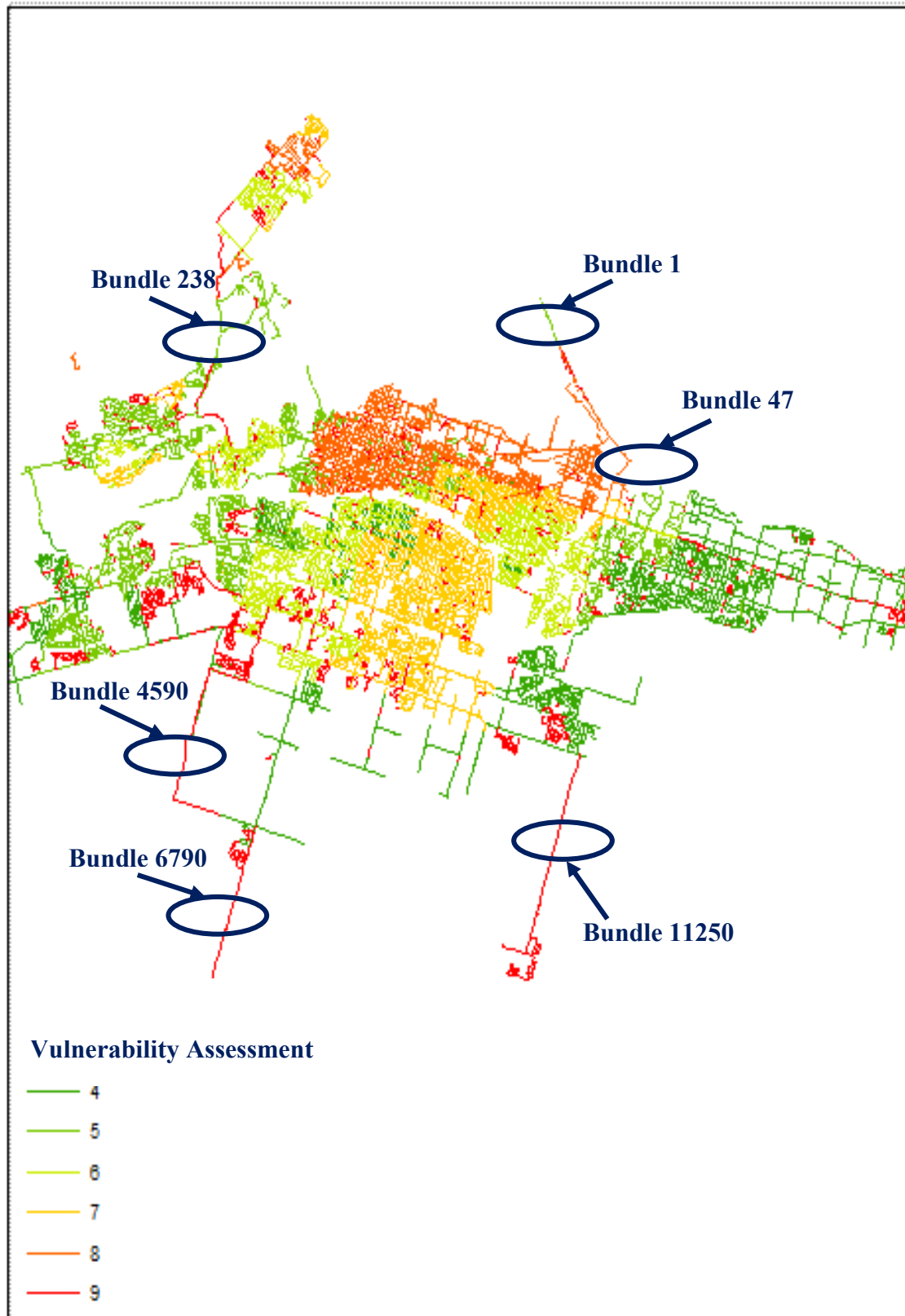
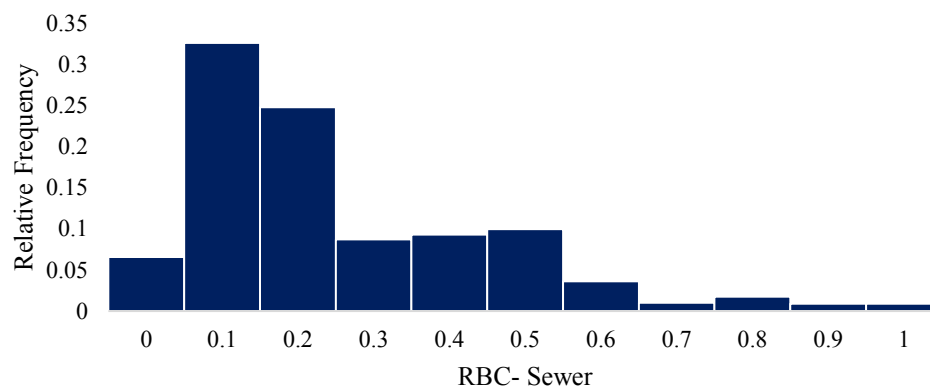


Figure 6-8 The best solution from the modified GA

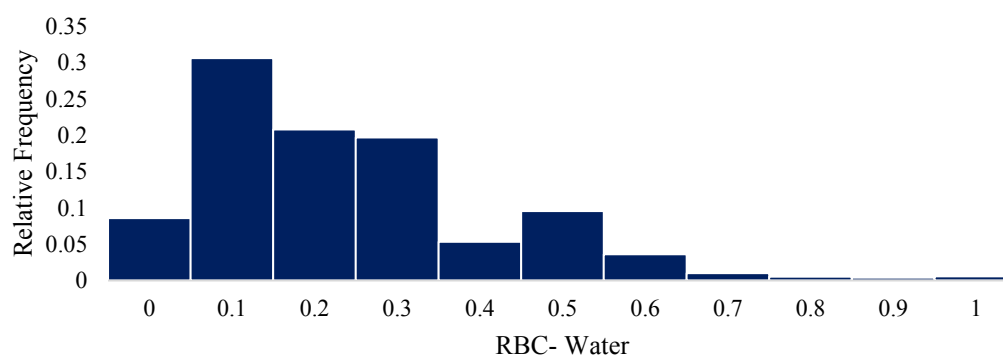
### **6.3.1 Interdependency Assessment**

Only 1895 road datasets, 9000 sewer datasets and 14500 water datasets were used after removing incomplete records. The same procedures were applied in this case study. For spatial module, the targeted layers for spatial interdependency analysis were water, sewer and road assets. The buffer length and width was the same as the first case study. The number of bundles constructed by this module was 10,500 bundles. The computational time was 39.5 sec. After performing the functional module analysis, RBC is imported back into ArcGIS geodatabase of the analyzed assets. The computational time for the functional module was 8.7 min.

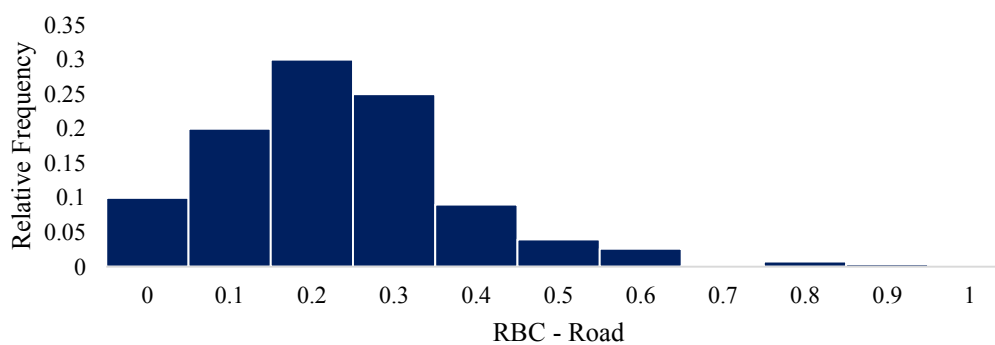
Figure 6-9 shows a comparison between the RBC histograms for water, sewer and road assets. The water and sewer networks are also skewed to the right and they have similar RBC histograms when compared to the water network of the City of Hamilton. The road network has also similar histogram when compared to the road network of the City of Hamilton. In both cases, road assets had better connectivity than water and sewer assets. Figure 6-9 shows a comparison between the RBC histograms for water, sewer and road assets. The water and sewer networks are also skewed to the right and they have similar RBC histograms when compared to the water network of the City of Hamilton. The road network has also similar histogram when compared to the road network of the City of Hamilton. In both cases, road assets had better connectivity than water and sewer assets.



a) Sewer



b) Water



c) Road

Figure 6-9 RBC histogram for water, sewer and road assets, London

### 6.3.2 Vulnerability Model

Table 6-5 shows a comparison between the outputs obtained using the MAUT model and the other two models (ANN and FCM). For the water network, the MSE was 13.71 for the FCM model and 11.74 for the ANN model. For the road network, the MSE was 18.05 for the FCM model and 8 for the ANN model. For the sewer network, the MSE was 34.1 for the FCM model and was 36 for the ANN model. For the City of London, the FCM model had an average MSE of 18.24 and the ANN model had an average MSE of 21.97. Figure 6-10 shows the results of the FCM model for the water network when being visualized inside the ArcGIS environment. The FCM model also showed better performance than the ANN model in mimicking experts' judgement in this case study.

Table 6-5 Comparison between the three models for City of London

Network	Percentages of assets in each rating (%)										
	Model	1	2	3	4	5	6	7	8	9	10
Water	MAUT	8	12	10	12	8	4	22	15	9	0
	ANN	12	10	8	9	14	7	17	21	2	0
	FCM	9	11	9	13	7	2	20	25	4	0
Road	MAUT	0	0	5	22	10	12	25	20	6	0
	ANN	0	0	4	14	20	22	25	15	0	0
	FCM	0	0	4	18	12	14	22	25	4	1
Sewer	MAUT	0	5	7	8	14	25	22	12	7	0
	ANN	0	0	5	14	20	20	15	21	3	2
	FCM	0	7	5	10	18	22	24	9	5	0

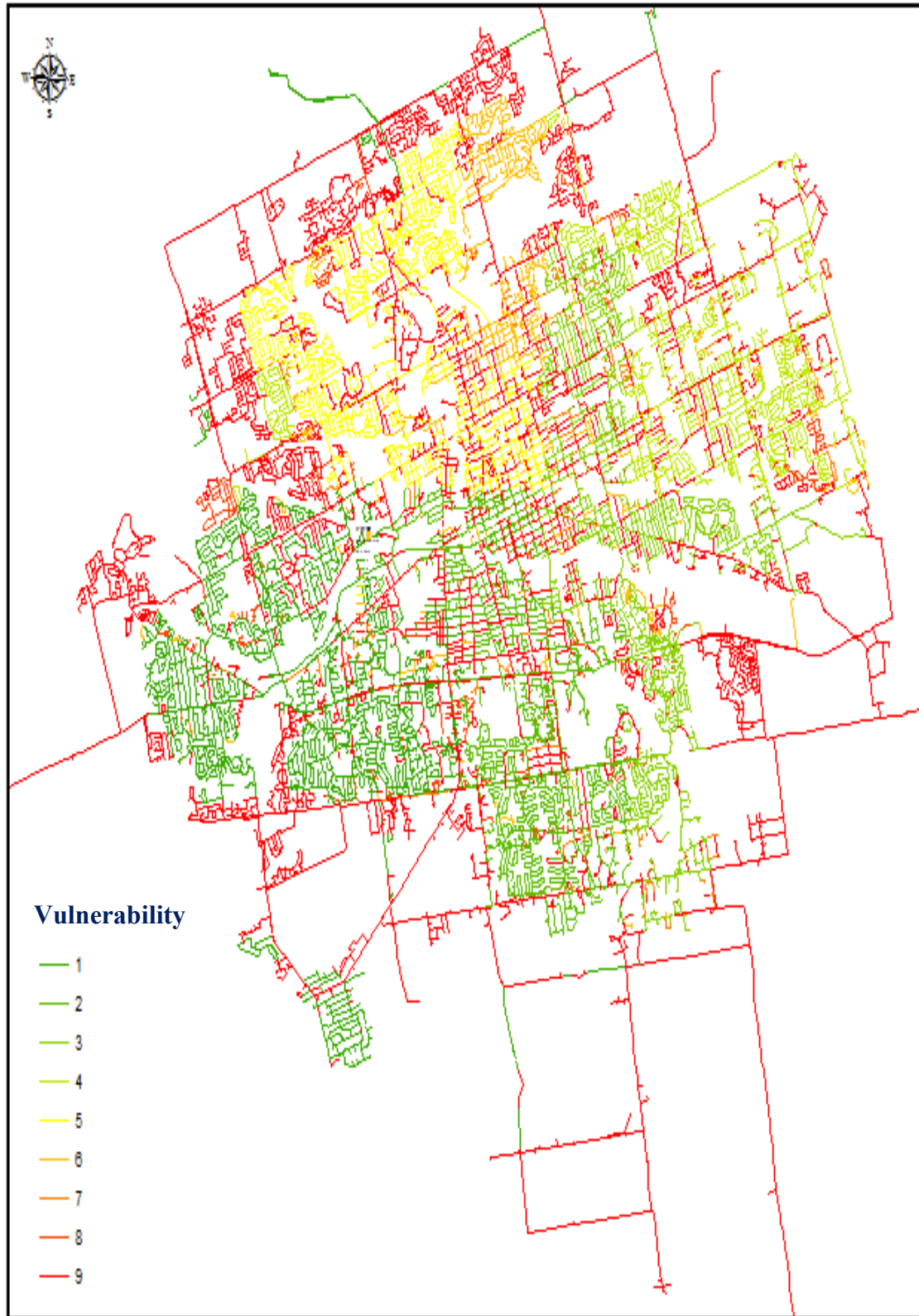


Figure 6-10 Vulnerability assessment for the water network using FCM

The FCM model is also used to construct fuzzy membership functions as shown in Figure 6-11. These member functions are constructed based on observed patterns in the analyzied datasets. Using the center of gravity defuzzification method, the decision maker can use generated memebership functions for each factor to rate vulneability of interdependent assets accounting for ambiguity in experts' input.

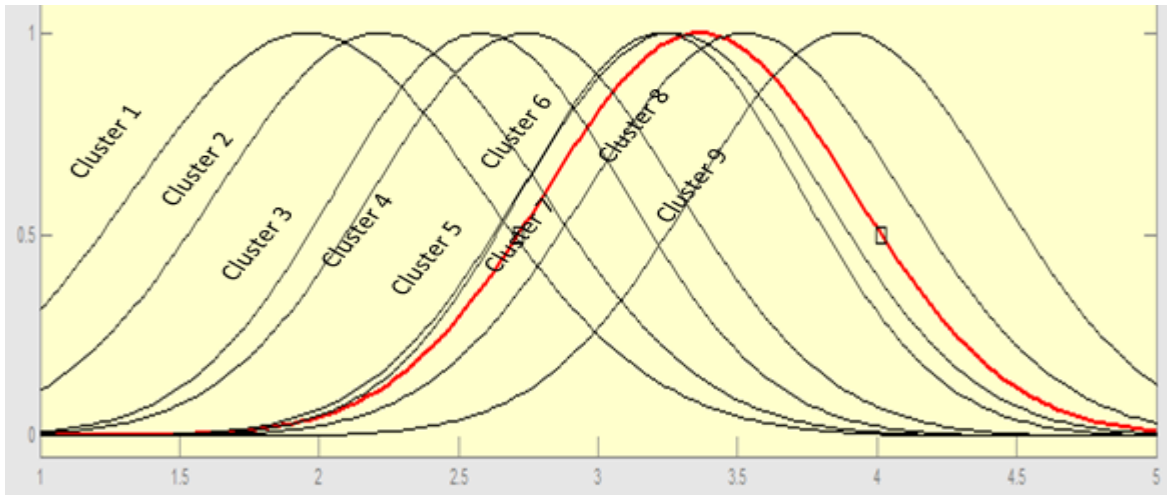


Figure 6-11 Vulnerability rating for water asset based on its condition

### 6.3.3 System Dynamics Model

To benchmark the performance of the modified GA against traditional GA, samples of bundles ranging from 100 to 10,500 were selected. For each sample of bundles, the time to reach the optimal solution was recorded for both GA types. The population size was 10,000, mutation rate was 0.4, crossover rate was 0.6 and number of trials was 1000. For 10,500 bundles, Figure 6-12 shows that the growth rate for the computational time needed to reach the optimal solution by modified GA is less than traditional GA by 47.2%.

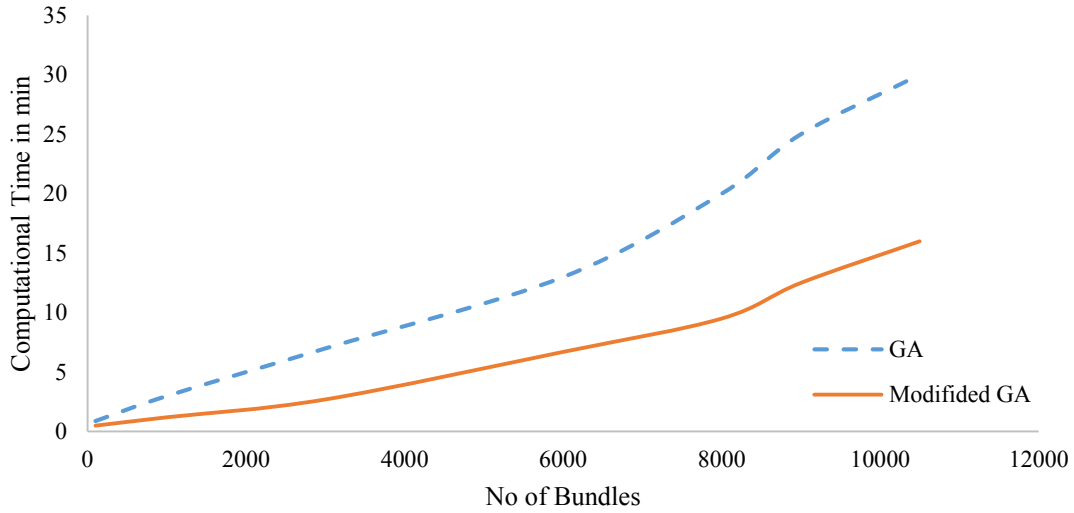


Figure 6-12 Comparison between traditional GA and modified GA

A sample for the best solutions obtained at the network level using the modified GA is show in Table 6-4. The best solution and its policies are shown in Figure 6-13. The assigned budget for the best solution was 738 M for 10,500 bundles. Solution 6 assigns better intervention polices for each bundle however the assigned budget exceeds the available budget (740 M) by 155 M. Appendix C has more details about the intervention actions taken within each policy.

Table 6-6 Sample for the best solutions obtained at the network level from the modified GA algorithm

Bundle ID	11	67	568	789	951	8510	Budget
Solution 1	Policy 9	Policy 7	Policy 10	Policy 3	Policy 8	Policy 9	738 M
Solution 2	Policy 6	Policy 3	Policy 9	Policy 5	Policy 6	Policy 9	789 M
Solution 3	Policy 4	Policy 2	Policy 8	Policy 6	Policy 3	Policy 8	815 M
Solution 4	Policy 2	Policy 5	Policy 7	Policy 7	Policy 5	Policy 5	835 M
Solution 5	Policy 5	Policy 2	Policy 4	Policy 4	Policy 2	Policy 4	858 M
Solution 6	Policy 2	Policy 1	Policy 3	Policy 2	Policy 1	Policy 2	895 M

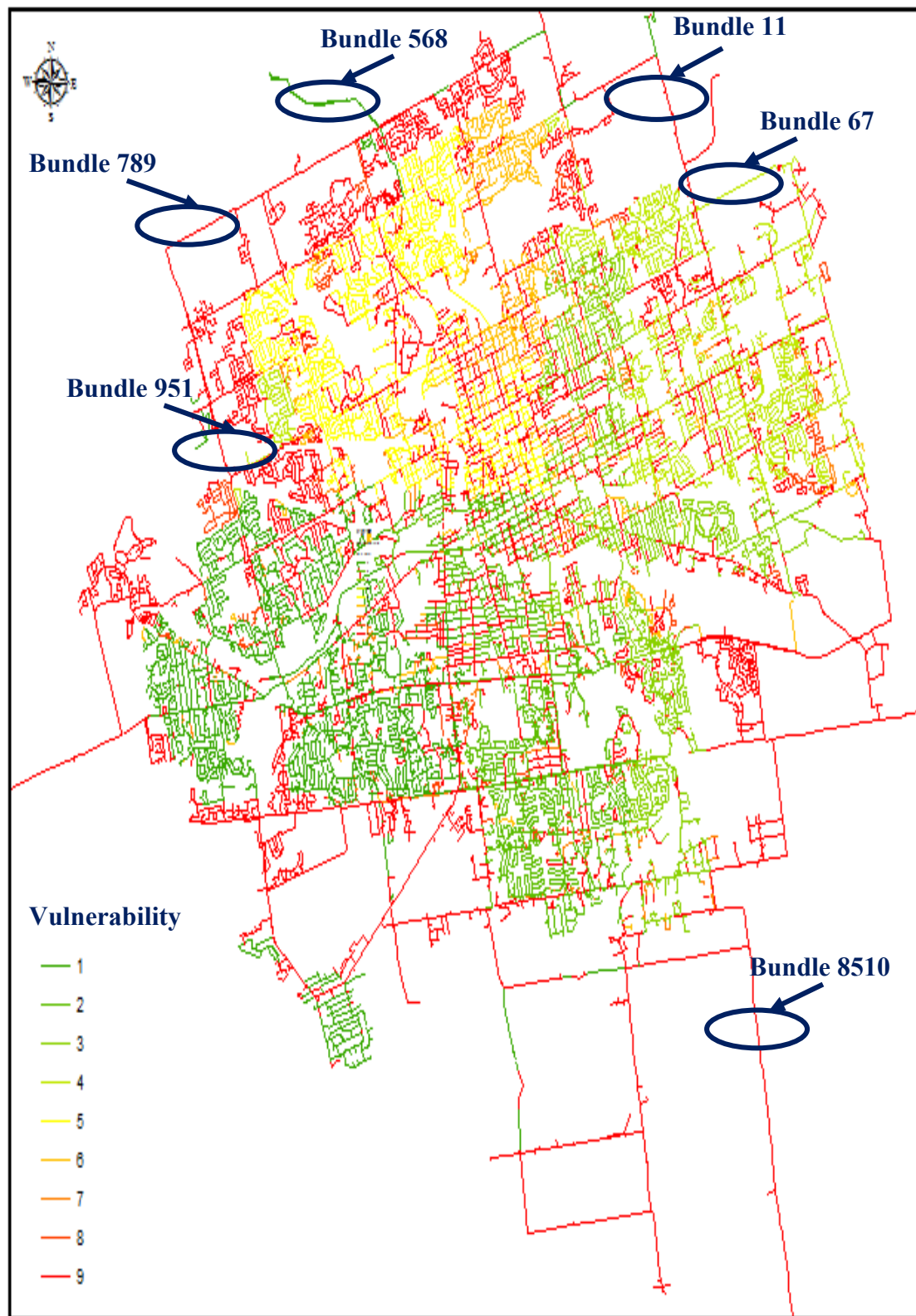


Figure 6-13 The best solution from the modified GA



## **6.4 Discussion of the Research Findings**

The spatial module was capable of constructing bundles of interdependent assets in timely fashion; 45.2 sec for the City of Hamilton and 39.5 sec for the City of London. For the functional module, results indicate that water and sewer networks have lower connectivity when compared to the road network in both cases. The computational time for the functional module was 10.5 min for the City of Hamilton and 8.7 min for the City of London.

For the vulnerability model, Table 6-7 shows a comparison between the three developed models for vulnerability assessment. Based on available datasets, the FCM model is the best technique for mimicking experts' judgment in rating vulnerability of interdependent assets.

For the MAUT model, it is easy to use and can be modified by other municipalities to suit their needs. The MAUT model may seem as favorable option in lack of enough historical data to build these data extensive models (ANN and FCM). However, the MAUT model suffers from some subjectivity as it considers experts' input for assessing vulnerability of interdependent water, sewer and road assets. The experts' input for constructing utility curves may not reflect all the observed patterns found in each dataset. In addition, the MAUT model does not consider ambiguity that exists in rating vulnerability of interdependent civil infrastructure assets due to experts' input. The MAUT model also requires extensive feedback from participants in the asset management with various backgrounds (operational, strategic and consultant) to construct an objective model.

Table 6-7 Comparison between the three models

	MAUT	ANN	FCM
Requires historical data	No	Yes ( $\geq 500$ )	Yes ( $\geq 500$ )
Analysis time	1.5 min	5 min	12 min
Experts' inputs	Yes	No	No
Black box	No	Yes	No
Subjective	Yes	No	No
Handle ambiguity	No	No	Yes
User-friendly	Yes	No	No
Average MSE	---	16.59	12.24

On the other hand, the ANN model utilizes self-organized mapping algorithm (SOM) to rate vulnerability of the interdependent assets based on recognized patterns in each dataset. The ANN model is a data driven model requiring sufficient amount of observed patterns, more than 500 datasets, and extensive effort in modeling with less involvement required from experts. The ANN model also lacks the ability to consider ambiguity due to experts' input.

The FCM model is also a data driven model requiring sufficient amount of observed patterns, more than 500 datasets, but accounts for ambiguity in rating vulnerability of interdependent assets. The computational time for the FCM model is 1.4 times the computational time for the ANN model.

The results of the developed vulnerability techniques were shared with three experts; one from the city of London and two from the City of Hamilton. Their feedback can be summarized in the following two points:

- The developed vulnerability techniques will be useful for staff to justify increases to intervention budgets to City Councils. Currently intervention actions are taken based on current condition of infrastructure assets without considering their neighbouring assets condition as well.

- In spite of the relatively complicated nature of the ANN and FCM models (AI models), the experts were relatively comfortable using these models. Both cities are relatively advanced in using asset management tools and currently has other systems based on MDP, Fuzzy Sets and the Analytical Hierarchy Process. Experts commented that this might not be the case with other municipalities that are still starting their asset management programs.

For the SD model, the experts agreed that the SD model is beneficial as a computational platform for exploring the effect of intervention policies at bundle and network level. They acknowledged that the model is flexible enough to add or remove variables based on the available data for each city. The experts however pointed out that the SD model can be enhanced by accounting for factors related to social and economic characteristics of their customers. Customers have different perceptions about expected LOS based on their age, income, social and political preferences. They are interested in computational platforms for objectively quantifying the effect of such factors on the integrated asset management approach. For the SD at bundle level, the performance was satisfactory for the experts as the model was capable of exploring large search space in few seconds. On the hand, the modified genetic algorithm can be enhanced more by the deployment of parallel computing techniques to decrease its computational time. They also suggested benchmarking GA performance against other exact and non-exact algorithms when using parallel computing techniques.

## **6.5 Summary and Conclusion**

This chapter described an analysis for the developed models on two case studies to optimize a value driven and near optimal intervention polices for civil infrastructure

networks considering their spatial and functional interdependencies. Three developed computational techniques were utilized to rate vulnerability of civil infrastructure systems considering their spatial and functional interdependencies with neighboring assets. The three computational models were; 1) MAUT, 2) ANN and 3) FCM. The FCM model showed strong performance in mimicking experts' judgement compared to ANN model. The experts were relatively comfortable using these models however they commented that this might not be the case with other municipalities that are still starting their asset management programs.

The SD was supplemented by a dynamic programming algorithm at the bundle level to find the best  $n$  intervention policies. This will aid in decreasing the need for sufficient experience in selecting a set of near optimum solutions. The SD was supplemented with modified GA algorithm to find near optimum intervention policies at network level. The modified GA utilized the set of optimum policies at bundle level provided by the SD and dynamic programming to seed its initial population. The SD model was capable of providing the decision maker with a platform to explore possible cost effective intervention policies for interdependent assets at bundle and network levels. A comparison between traditional and modified GA was presented to show the effect of the added enhancements on decreasing the computational time. The experts pointed out 1) the need for integrating more factors about social and economic characteristics of their customers, 2) the modified genetic algorithm can be enhanced more by parallel computing techniques to decrease its computational time and 3) they also suggested benchmarking GA performance against other exact and non-exact techniques when using parallel computing techniques.

# **Chapter 7 : CONCLUSIONS AND FUTURE WORKS**

## **7.1 Summary and Conclusions**

Current decision support systems for infrastructure management are implemented ignoring spatial and functional interdependencies that exist between water, sewer and road network assets. This research presents a framework for optimizing intervention policies for municipal infrastructure assets considering spatial and functional interdependencies as well as vulnerability of these networks. The developed research framework consists of three models; 1) interdependency assessment model, 2) vulnerability assessment model and 3) system dynamics model.

The interdependency assessment model captures interdependent assets by utilizing two modules: spatial interdependency module and functional interdependency module. The spatial module was developed and coded using python programming language in ArcGIS environment; making use of its geoprocessing tools in determining geographically interdependent assets. The spatial module encapsulates the interdependent assets in a set of newly developed layers and a newly generated database containing essential characteristics of such interdependencies. On the other hand, the functional module employs principles of graph theory in determining an asset's degree of connectivity with its neighboring assets. The functional module will aid in recognizing the likely influence of an asset failure on its neighboring assets' performance using “betweenness centrality”. The functional module was also implemented using python and was embedded in ArcGIS to facilitate the analysis of large scale networks.

The output of the interdependency assessment model is in the form of bundles of spatially and functionally interdependent assets.

For vulnerability assessment, the research investigated the use of three computational techniques to rate vulnerability of civil infrastructure systems considering their spatial and functional interdependencies with neighboring assets. The three developed computational models were; 1) multi-attribute utility theory (MAUT), 2) artificial neural network (ANN) and 3) fuzzy c-mean clustering (FCM). Operation and maintenance reports obtained from two Canadian municipalities, Cities of London and Hamilton, Ontario, were used to select factors influencing the vulnerability of water, sewer and road assets. For the MAUT model and based on the identified factors from operation and maintenance reports, surveys were sent to experts and their feedback was elicited to construct utility functions to rate the vulnerability of interdependent assets. On the other hand, the ANN model utilizes self-organized mapping algorithm (SOM) to rate vulnerability of these assets based on recognized patterns in each dataset. The ANN model is a data driven model requiring sufficient amount of observed patterns and extensive effort in modeling with less involvement required from experts. On the other hand, the FCM model is capable of accounting for ambiguity and imprecision associated with experts' inputs in rating vulnerability of interdependent assets. Based on the available datasets, the FCM model outperformed the ANN model in mimicking experts' knowledge for rating vulnerability of interdependent assets as was shown in Chapter 6. The algorithms for FCM and ANN models were developed and implemented using MATLAB programming language inside MATLAB 2013. The MAUT model was developed and implemented inside the Excel environment.

Subsequently, the system dynamics (SD) model was developed to find cost effective intervention policies accounting for interdependent infrastructure assets to meet customers' expectations and decrease assets' vulnerability. The SD model consists of 23 variables and 8 causal feedback loops; two extracted from the literature and the rest were constructed based on four unstructured interviews with three experts. Two optimization algorithms were augmented with SD to find optimal intervention policies at bundle and network levels respectively. These algorithms are 1) dynamic programming algorithm, 2) single objective genetic algorithm (GA). Two case studies were presented to demonstrate the application of the developed framework and its expected contributions using data obtained from the Cities of London and Hamilton, Ontario. The SD model was capable of providing decision makers with a platform to explore possible cost effective intervention policies and examine a number of generated scenarios. Three enhancements were introduced to the developed GA algorithm; 1) filtering query-based function to minimize the computational time, 2) adding a dynamic memory to store worst solutions to prevent regeneration of these solutions in subsequent trials and 3) modifying the mutation function to act as local search procedure to improve the convergence rate of GA. A comparison between the traditional and modified GA was presented to show the effect of the added enhancements. Validation of these models was discussed in Chapter 6.

## **7.2 Research Contribution**

The contributions of this research are:

- 1- For the interdependency assessment model; development of an automated model to construct bundles of interdependent assets

inside ArcGIS 10 using python. The model utilises available geoprocessing tools inside ArcGIS™ to encapsulate spatially interdependent assets and then assesses their functional interdependencies using betweenness centrality as described in Chapter 4.

- 2- For data collection; in-depth analysis of two datasets from two case studies was conducted in order to understand current practices and assist in the design of the developed framework and subsequently in testing and validating the developments made.
- 3- For the vulnerability assessment model; development and implementation of three computational models (FCM, ANN and MAUT) to rate vulnerability of interdependent assets and rating their respective performance. Implementation of the algorithms for FCM and ANN models was carried out in MATLAB™ 2013. The MAUT was developed and implemented in MS Excel™ 2013 environment.
- 4- For the SD model; development and implementation of an automated SD model to find cost effective intervention actions accounting for interdependent assets. The developed SD model is capable of generating intervention policy reports in three granularities (i.e. single asset level, bundle level and network level). This model constitutes several contributions:



- 1) Developing a SD model for integrated asset management as described in Chapter 4. While limited number of interviews (i.e. four interviews) were conducted to build the SD model, it can be used as a proof of concept on how SD can be developed and implemented to find cost effective intervention policies. Six feedback loops were constructed based on these interviews.
- 2) Supplementing the SD model with a dynamic programming algorithm to optimize intervention policies at the bundle level. When using SD only, sufficient knowledge and experience are required to select a set of near optimal solutions that cope with decision makers' preferences. Supplementing the SD model with a dynamic programming algorithm will overcome such limitations.
- 3) Supplementing the SD model with the developed GA algorithm to aid decision makers in finding near optimum intervention policies at network level. The developed GA algorithm is enhanced by; 1) filtering query-based function, 2) dynamic memory and 3) modifying the mutation function to act as local search procedure.

### **7.3 Limitations**

The limitations of the developed research framework are:

1. For the vulnerability model, the performance of the developed three models needs to be benchmarked against other unsupervised learning algorithms.
2. For the SD model, it was constructed based on four unstructured interviews. More interviews are required to expand the SD model and enhance its structure. Also, the performance of the two developed optimization algorithms need to be benchmarked against other exact and non-exact optimization algorithms.
3. For vulnerability and SD models; the developed models were tested and validated using two case studies. Further validation is needed to measure the performance of these developed models on other case studies. This will improve the generality of the developed models and its robustness.

## **7.4 Future Work**

The following are some recommendations for future work:

- 1- Analyzing more operation and maintenance reports from other cities to enhance the robustness of the developed vulnerability model with more inputs.
- 2- Utilizing parallel computing techniques to decrease further the computational time needed for finding optimum intervention policies at network level.
- 3- Conducting more interviews to elicit additional experts' knowledge to expand the SD model and enhance its structure.
- 4- Investigating how condition assessment polices can be integrated along with intervention polices to establish more comprehensive framework for managing interdependent infrastructure networks.

- 5- Exploring and understanding the relationship between interdependency assessment, vulnerability assessment and risk assessment or reliability assessment.

## References

- Abbott, D. (2005). "Practical Considerations in the Selection and For the Use of Microtunneling Vs Other Trenchless Techniques." North American Society for Trenchless Technology (NASTT) NO-DIG. 1. Orlando, Florida, USA: ASCE.
- Achim, D., Ghotb, F., & McManus, K. J. (2007). "Prediction of Water Pipe Asset Life Using Neural Networks". *Journal of Infrastructure Systems*, 13, 26-30.
- Arboleda, C. (2006). "Vulnerability Assessment of the Operation of Health Care Facilities during Disaster Events". Thesis submitted to Purdue University, Indiana, USA
- Atef, A. and Moselhi, O. (2014) "Optimizing Intervention Policies for Civil Infrastructure Networks Using System Dynamics". *Journal of Performance of Constructed Facilities* (under review)
- Atef, A. and Moselhi, O. (2014) "Vulnerability Assessment of Civil Infrastructure Networks Considering Spatial and Functional Interdependencies". *Journal of Pipeline Systems Engineering and Practice* (under review)
- Atef, A., and Moselhi, O. (2014). "Modeling spatial and functional interdependencies of civil infrastructure networks". ASCE 2014 Pipelines Conference, Portland, Oregon, USA.
- Atef, A., and Moselhi, O. (2013). "Budget Allocation for Vulnerable and Interdependent Civil Infrastructure Networks". 4th Construction Specialty Conference, Canadian Society for Civil Engineering. Montreal: CSCE.

- Baker, G. H. (2003). "A Vulnerability Assessment Methodology for Critical Infrastructure Facilities.". National Capital Region Critical Infrastructure Vulnerability.
- Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (1994). "At Risk: Natural hazards, People's vulnerability, and disasters." London, Routledge.
- Buckley, W. S. (2005). "Fuzzy expert systems and fuzzy reasoning.". Wiley, N.J., USA
- Crucitti, Paolo, et al. "Error and attack tolerance of complex networks." *Physica A: Statistical Mechanics and its Applications* 340.1 (2004): 388-394.
- Dudenhoeffer, D., Permann, M., & Manic, M. (2006). "CIMS: a framework for infrastructure interdependency modeling and analysis." *Proceedings of the 2006 Winter Simulation Conference*. Monterey, CA: IEEE.
- Earl, E. L., Mitchell, J. E., & Wallace, W. A. (2004). "Assessing Vulnerability of Proposed Designs for Interdependent Infrastructure.". *Proceedings of the 37th Hawaii International Conference on System Sciences*. 1. Hawaii: IEEE.
- Eun, H. O., Abhijeet, D., & Makarand, H. (2010). "Vulnerability Assessment of Critical Infrastructure, Associated Industries, and Communities during Extreme Events.". *Construction Research Congress 2010*. Banaf: ASCE.
- Ezell, B. (2004). "Quantifying Vulnerability to Critical Infrastructure Systems". Ph.D. Dissertation. , Department of Engineering Management, Old Dominion University.
- Fahmy, M., & Moselhi, O. (2009). "Forecasting the Remaining Useful Life of Cast Iron Water Mains". *Journal of Performance of Constructed Facilities*, 23(4), 269–275

Fares, H. (2005). "Evaluating the Risk of Water Main Failure Using a Hierarchical Fuzzy Expert System". Montreal: M.Sc. Thesis, Department of Building, Civil and Environmental Engineering, Concordia University.

Flax, L. K., Jackson, R. W., & Stein, D. N. (2003). Community Vulnerability Assessment Tool Methodology. *Natural Hazards Review*, 3(4), 163-176.

Shahata, Khaled Farouk (2013). "Decision-Support Framework for Integrated Asset Management of Major Municipal Infrastructure." PhD thesis, Department of Building, Civil and Environmental Engineering, Concordia University.

Gesara, S., & Dueñas-Osorio, L. (2010). Synthesis of Modeling and Simulation Methods on Critical Infrastructure Interdependencies. *Sustainable and Resilient Critical Infrastructure Systems Simulation Modeling and Intelligent Engineering*, 1-51.

Godschalk, D. R. (2003). "Urban Hazard Mitigation: Creating Resilient Cities." *Natural Hazards Review*, 4(3).

Haines, Y. Y. (2009). "Risk Modeling, Assessment, and Management" Wiley, New York, USA

Haines, Y., & Jiang, P. (2001). "Leontief-Based Model of Risk in Complex Interconnected Infrastructures". *Journal of Infrastructure Systems*, 7(1), 1-12.

Hastak, M. a. (2002). "System for Evaluating Underground Pipeline Renewal Options". *Journal of Infrastructure Systems*, 7(6), pp. 105-113.

Hegzay, T., & Ayed, A. (1998). "Neural Network model of parametric cost estimation of highway projects". *Journal of construction and Engineering Management*, 124(3), 210-218.

Hillier, F. S., & Lieberman, G. J. (2004). "Introduction to Operations Research". McGraw-Hill, New York, USA

InfraGuide. (2003). "Developing Levels of Services." Ottawa, Canada: DMIP Best Practice, National Research Council of Canada.

Infraguide. (2003). "Selection of Technologies for Sewer Rehabilitation and Replacement." Ottawa, Canada: DMIP Best Practice, National Research Council of Canada.

Ishizaka, A., & Nemery, P. (2013). "Multi-attribute utility theory". *Multi-Criteria Decision Analysis: Methods and Software*, 81-113.

Karmakar, S., Simonovic, S. P., Peck, A., & Black, J. (2010). "An Information System for Risk-Vulnerability Assessment to Flood". *Journal of Geographic Information System*, 2, 129-146.

Khan, H., Vasilescu, L. G., & Khan, A. (2011). "Disaster Management Cycle – A Theoretical Approach". *Management and Marketing Journal*, 1-8.

Khan, Z., Zayed, T., & Moselhi, O. (2010). "Structural Condition Assessment of Sewer Pipelines". *Journal of Performance of Constructed Facilities*, 24(2), 250-265

Laucelli, D. and Giustolisi, O. (2014). "Vulnerability Assessment of Water Distribution Networks under Seismic Actions." *J. Water Resources. Planning and Management*.

Macal, C. M., & Macal, C. M. (2005). "Tutorial on Agent-Based Modeling and Simulation". Proceedings of the 2005 Winter Simulation Conference, (pp. 2-15). Orlando, FL, USA.

Macal, C. M., & North, M. J. (2006). "Tutorial on Agent-Based Modeling and Simulation Part 2: How to Model with Agents". Proceedings of the 2006 Winter Simulation Conference (pp. 73-83). Monterey, CA: IEEE.

Mandapaka, V., Basheer, I., Sahasi, K., Ullidtz, P., Harvey, J., and Sivaneswaran, N. (2012). "Mechanistic-Empirical and Life-Cycle Cost Analysis for Optimizing Flexible Pavement Maintenance and Rehabilitation." *Journal of Transportation Engineering*, 138(5), 625–633.

Moselhi, O., Hammad, A., Alkass, S., Assi, C., Debbabi, M., & Haider, M. (June 2-4, 2005). "Vulnerability Assessment of Civil Infrastructure Systems: A Network Approach." 1st CSCE Specialty Conference on Infrastructure Technologies, Management and Policy. Toronto, Ontario, Canada.

Moselhi, O., Hegazy, T., & Fazio, P. (1991). "Neural Networks as Tools in Construction". *Journal of Construction Engineering and Management*, 117(4).

NOAA. (2002). "Vulnerability Assessment". National Oceanic and Atmospheric Administration.

Orabi, W. and El-Rayes, K. (2012). "Optimizing the Rehabilitation Efforts of Aging Transportation Networks." *Journal of Construction and Engineering Management*, 138(4), 529–539.



Osman, H., & Ali, M. R. (2012). "Complex Systems Modeling of Infrastructure Assets, Operators, Users, and Politicians using System Dynamics". Construction Research Congress 2012. West Lafayette, Indiana: ASCE.

Ouyang, M., Hong, L., Maoa, Z.-J., Yu, M.-H., & Qi, F. (2009). "A methodological approach to analyze vulnerability of interdependent infrastructures." *Simulation Modelling Practice and Theory*, 17, 817–828.

Richard Robinson, U. D. (1998). "Road Maintenance Management (Vol. 1)." Macmillan, Birmingham, UK

Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). "Identifying, understanding, and analyzing critical infrastructure interdependencies." *IEEE Control Systems Magazine*, 21(6), 11-25.

Roshani, E. and Filion, Y. (2014). "Event-Based Approach to Optimize the Timing of Water Main Rehabilitation with Asset Management Strategies." *Journal of Water Resources Planning and Management*, 140(6), 123-135

Ross, T. J. (2010). "Fuzzy logic with engineering applications". Wiley, Chichester, U.K.

Salman, B. (2010). "Infrastructure Management and Deterioration Risk Assessment of Wastewater collection systems." Ph.D. submitted to the Department of Civil and Environmental Engineering, University of Cincinnati, USA.

Santos, J., & Haines, Y. (2004). "Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures." *Risk Analysis*, 24(6), 1437–1451.

SOI Report (2005) “City of Hamilton State of the Infrastructure Report”. Available Online at

<http://www.myhamilton.ca/myhamilton/CityandGovernment/CityDepartments/PublicWorks/CapitalPlanning/Asset+Management/State+of+the+Infrastructure+Report.htm>

Stapelberg, R. F. (2011). “Infrastructure Systems Interdependencies and Risk Informed Decision Making (RIDM): Impact Scenario Analysis of Infrastructure Risks Induced by Natural, Technological and Intentional Hazards”. Journal of Systems, Cybernetics and Informatics, 9(5).

Sterman, J. D. (2000). “Business Dynamics: Systems Thinking and a Modeling for a Complex World.” McGraw-Hill Higher Education, New York, USA

Taha, H. A. (20008). “Operations Research: An Introduction” Prentice Hall, New York USA

Talbi, E.-G. (2009). “Metaheuristics: From Design to Implementation” Wily, New York, USA

Wei, J., Kong, Y., and Fu, Z. (2009). “Multi-Objective Optimization for Pavement Maintenance and Rehabilitation Strategies.” International Conference on Transportation Engineering, pp. 2919-2924.

Weichselgartner, J. (2001). “Disaster mitigation: the concept of vulnerability revisited”. Disaster Prevention and Management, Volume 10(Number 2), 85-94.

Wu, L., Wen, Y., Zhou, C., Xiao, C., and Zhang, J. (2014). "Modeling the Vulnerability of Waterway Networks." *Journal of Waterway, Port, Coastal and Ocean Engineering*, 140(4), 45-56.

Yuan, G. J. (1995). "Fuzzy sets and fuzzy logic: theory and applications." Upper Saddle River, N.J.: Prentice Hall.

Zadeh, L. (1965). "Fuzzy sets." *Information Theory*, 8(3), 338–353.

Zhu, K. J., Su, S. H., & Li, J. L. (2005). "Optimal number of clusters and the best partition in fuzzy C-mean". *Systems Engineering-theory & Practice*, 3, 52-65

## **Appendix A : Fuzzy Set Theory**

Fuzzy logic and fuzzy rule based systems, which are based on fuzzy logic, offer an approach for reasoning which can encapsulate the imprecision in rules and model assertions conveyed by human experts (Buckley, 2005). Fuzzy logic enables reasoning using approximations but this does not imply vague or fuzzy outputs for problem solutions as the imprecisely identified inputs are transformed into precise numerical inputs which produce precise numerical outputs (Ross, 2010). Fuzzy logic and systems based on it are an actively investigated topic in many fields including engineering and computer science, business and management, psychology, philosophy, and mathematics. Roughly, Fuzzy system applications may be grouped into two categories (Yuan (1995), Buckley (2005)):

1. Fuzzy control systems
2. Fuzzy decision support systems

A control system continuously receives sensor for inputs (i.e. speed, distance, temperature, pressure...etc.) and employ these inputs to adjust various output variables (i.e. amount of electric current flowing into an electric motor, rate of fuel supply to an engine ....etc.) (Buckley, 2005). The fuzzy control systems are implemented to attain a smoother and efficient operation, for example, a self-regulated air conditioner that maintains desirable temperature and humidity with less fluctuation and greater energy efficiency (Buckley, 2005). On the other hand, fuzzy decision support systems are utilized to make decision based using the knowledge base that fuzzifies, aggregates and defuzzified the inputs to single or multiple decision outputs.

The steps needed to formulate a fuzzy system are summarized in Figure A-1. The following sections clarify the foundation of fuzzy set theory and illustrate comprehensively the various necessary steps to establish fuzzy expert system.

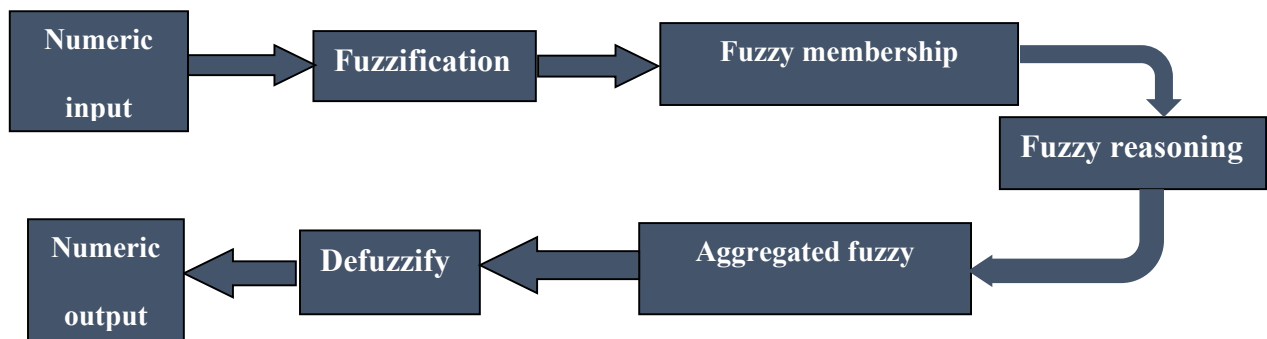


Figure A-1 Fuzzy expert system steps

## Fuzzy Sets and Crisp Sets

In classical logic, the boundary between what is in a set and what is outside is crisp or sharp. For instance, all people with height bigger than 180cm are considered in the set of very tall people. Anyone less than 180cm is not in the set of tall people even if that person is 179cm and because of the sharpness of the set boundary, such sets are known as crisp sets. As the domain (in this case the height) value increases, the degree of membership in the set tall people remains false (zero), but suddenly jumps to (1) true as height reaches 180cm as shown in Figure A-2.

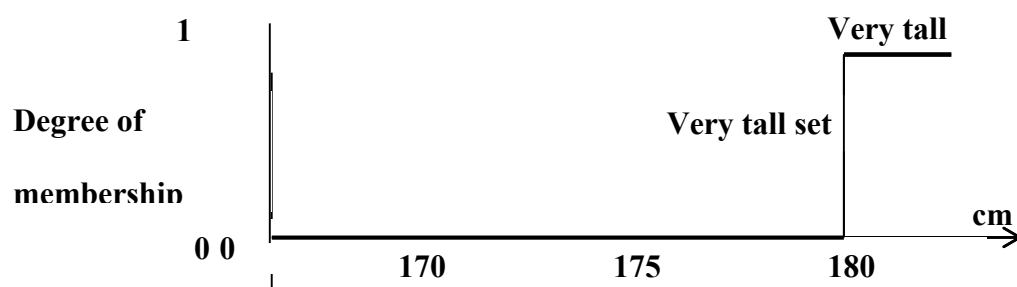


Figure A-2 Crisp set in classical logic (Yuan, 1995)

For a fuzzy set, the membership value lies within the range zero (no membership) to 1 (complete membership). For example, the membership graph of the fuzzy set very tall people may have the shape shown in Figure A-3. According to this membership function, someone with height of 175cm will have a membership value of 0.5, and a height of 179 will have a membership value of 0.9. All heights at or below 170 cm will have the membership value zero and all those at or above 180 will have membership value 1.

Figure A-4 shows the membership functions of three fuzzy sets examples; medium, tall and very tall. These three membership functions are bell-shaped. Depending on the application, data availability and experts' opinions, fuzzy set membership functions can have different shapes including S-shape, triangle, and trapezoid....ect. By allowing continuous valued degrees of membership, fuzzy sets enable the handling of imprecise concepts which are commonly encountered in real life problems.

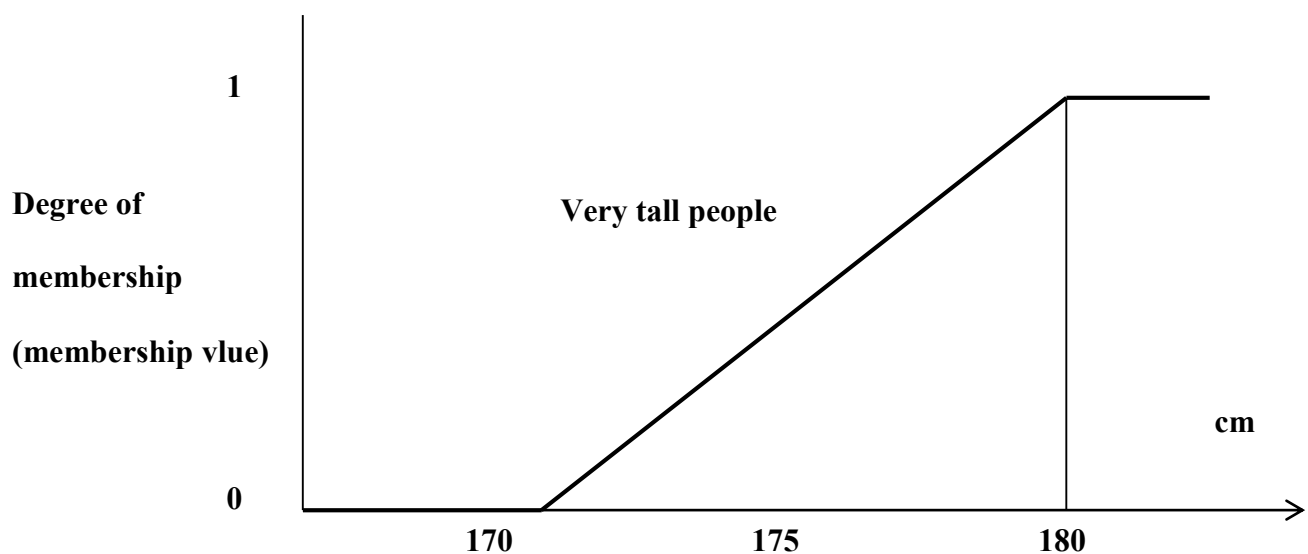


Figure A-3 Fuzzy membership function for very tall people (Yuan, 1995)

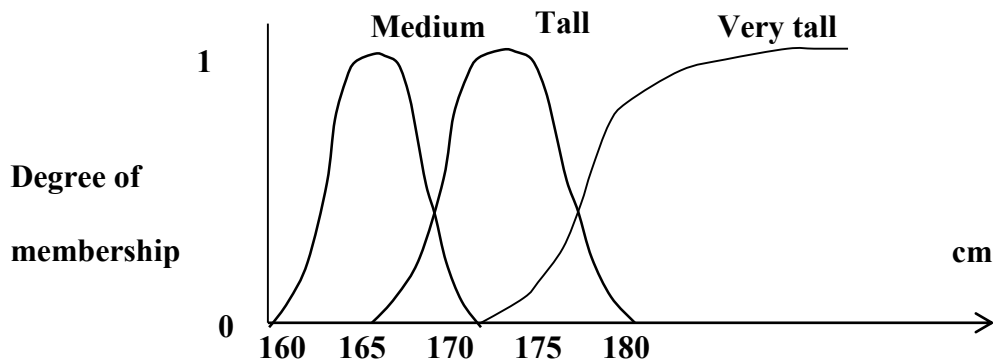


Figure A-4 Fuzzy membership function for medium, tall and very tall people (Yuan, 1995)

## Fuzzy Logic and Probability Theory

There has been a lot of discussion about the nature of fuzzy logic ever since it appeared in the 70s by Zadeh (1965). Many are quite dismissive about fuzzy logic and regard it as just a form of probability and despite their apparent similarity; there is an important difference between the two paradigms (Yuan, 1995). Both fuzzy logic and probability deal with the issue of uncertainty. Both use a continuous 0 to 1 scale for measuring uncertainty, but with a fundamental difference. Probability deals with likelihood – the chance of something happening or something having a certain property. Fuzzy logic deals not with likelihood of something having a certain property, but the degree to which it has that property (Buckley, 2005). For instance, if a fair coin is tossed one time, both tail and head have an equal probability of 0.5. In this context, the probability attempts to predict the likelihood of it landing with the head or tail face up. When the coin has landed, there is nothing ambiguous about the outcome of the tossing and therefore the probability is no longer applicable, nor necessary. On the other hand, consider a badly defaced coin, there would be uncertainty as to whether a face is actually the head or the tail (Yuan, 1995). It is in this situation that fuzzy logic plays its role by stating the degree to which the face in question might be the head

or tail. In other words, fuzzy logic concerns not the likelihood of the event (head or tail), but the degree to which the event has happened (possibility) (Yuan, 1995).

## **Fuzzy reasoning**

The fuzzy model of a problem consists of a series of unconditional and conditional fuzzy propositions. These are similar in form to those in conventional expert systems. An unconditional fuzzy proposition has the form

$$a \text{ is } B$$

Where ‘ $a$ ’ is a linguistic variable and  $B$  is the name of a fuzzy set. ‘ $a$ ’ is called a linguistic variable because its value in the proposition is expressed by a human expert using a word (linguistic expression) rather than a number. For example:

‘Pipe condition is low’

During the reasoning process, the truth value of this proposition is given by the degree of membership of pipe condition in the fuzzy set low. This membership value is computed from the actual case-specific numeric value with which pipe condition is instantiated, and the fuzzy membership function low. A fuzzy conditional proposition or rule has the form

$$\text{IF } a \text{ is } B \text{ THEN } c \text{ is } D$$

It is interpreted as: ‘ $a$ ’ is a member of ‘ $B$ ’ to the degree that ‘ $c$ ’ is a member of ‘ $D$ ’. In other words, the consequent (RHS) of the rule is applied or executed only to the extent that the antecedent (LHS) is true. For example in the rule

IF pipe condition is fair THEN risk is high



The membership value of risk in the fuzzy set high is determined by the membership value of pipe condition in set fair. So for example, if the antecedent has a truth value of 0.5, the strength of the consequent will also be 0.5, and the fuzzy region<sup>1</sup> for the set high for risk will be truncated to level 0.5. In reasoning using fuzzy logic, a number of fuzzy propositions is evaluated for their degrees of truth, and all those having some truth contribute to the final output state of the solution variable (Buckley, 2005). Unlike conventional expert systems, where statements are executed serially, fuzzy logic systems are based on the parallel processing principle. In other words, all rules are fired even if not all of them contribute to the final outcome and some may contribute only partially. For example, in determining the value of the solution variable *risk* in the above example, the contribution of the rule to making it *high* will be to a degree of 0.5.

IF pipe condition is fair THEN risk is high

A number of other rules may also contribute to varying degrees to the truth value of a high risk. All these truth values, represented visually by corresponding fuzzy regions, are combined to give the aggregate truth value for high risk (min-max rule). There will also be other rules which will be fired to give truth values for propositions risk is medium and risk is low. The ultimate solution value of the variable risk is determined once again through a combination process, this time aggregating the fuzzy spaces for high, medium and low risk.

The numerical output value for a solution variable is computed from the aggregated fuzzy output region through a process known as defuzzification. Although the reasoning process is performed using fuzzy rules and inference, the values input by the user and that produced by the fuzzy system are non-fuzzy numerical values. The input values are fuzzified (converted into

---

<sup>1</sup> The fuzzy region of a set is the area covered by its membership graph.

various fuzzy set membership values) to allow fuzzy reasoning, and then the resulting fuzzy (set membership) values are transformed into exact numerical values to make them applicable to the problem at hand.

### **Min-Max rule**

Fuzzy rules of inference are used to combine the fuzzy regions produced by the application of many rules run in parallel. The most common rule for this purpose is known as the min-max rule. The consequent region of a fuzzy rule is restricted to the antecedent (LHS) truth or membership value. Given the fuzzy rule:

IF pipe condition is fair THEN risk is high

If the membership value of pipe condition in X is 0.5, then the degree of truth of the consequent (membership value of risk in high) will be 0.5. When the LHS of the rule consists of a number of fuzzy propositions, the composite membership value of the LHS is the minimum of the memberships of all of the propositions on the LHS. This minimum truth value from the LHS is applied to that of the consequent (RHS). As an example, given the rule:

IF pipe condition is fair AND pipe diameter is large THEN risk is high

If the membership value of pipe condition in fair is 0.5, and that of pipe diameter in large is 0.2, the degree of truth of the consequent (membership value of risk in high) will be 0.2. If a number of rules lead to different membership values for an output variable, the maximum of these values is taken as the membership value. For example, given a number of rules producing different truth values  $T_1, T_2, \dots, T_n$  for the membership of risk in high, the aggregated truth value is  $\text{maximum}(T_1, T_2, \dots, T_n)$ . For example if application of the following rules lead to differing membership values (shown in parentheses) for the output variable risk in the fuzzy set medium:

- IF pipe condition is good THEN risk is medium (0.3)
- IF traffic load is medium THEN risk is medium (0.2)
- IF soil is loose THEN risk is medium (0.8)

Then, variable risk will have a membership value of  $\max(0.3, 0.2, 0.8)$  is 0.8 in medium.

## Defuzzification

With the application of a host of similar rules for the pipe risk in the above example, the membership values for risk in the low and high sets will also be similarly evaluated using the min-max rules. Suppose these values are 0.4 for small, 0.8 for medium, and 0.2 for high. These membership values will truncate the fuzzy spaces for the sets small, medium and high. These fuzzy regions are combined to give the aggregated fuzzy space for the output variable risk as shown below.

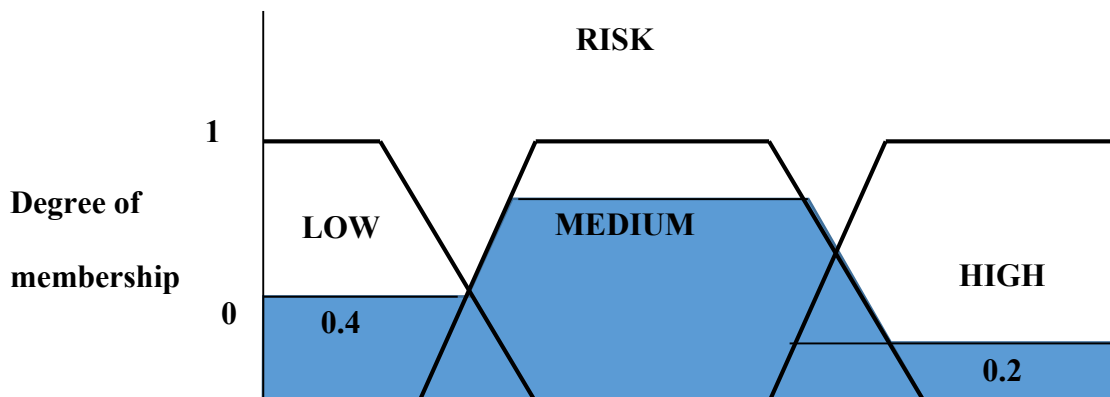


Figure A-5 Defuzzification process

Defuzzification is the process of taking the aggregated fuzzy region for the output variable – in this case risk, and assigning an exact numerical value to it. There are a number of methods of doing this, and the most common one among them is known as the clipped centroid or centre of

gravity method. The centre of gravity is simply the weighted average of the output membership function. The result R is calculated using the formula:

$$R = \frac{\sum_{i=0}^n d_i \cdot m(d_i)}{\sum_{i=0}^n m(d_i)} \quad \dots\dots\dots \text{Equation A-1}$$

Where  $d_i$  is the  $i^{\text{th}}$  domain value,  $m(d_i)$  is the membership value for that domain point. In this example, the domain in question is that of the variable risk, with  $i^{\text{th}}$  in the range  $[0,100]$ . The diagram below illustrates the centroid method of defuzzification.

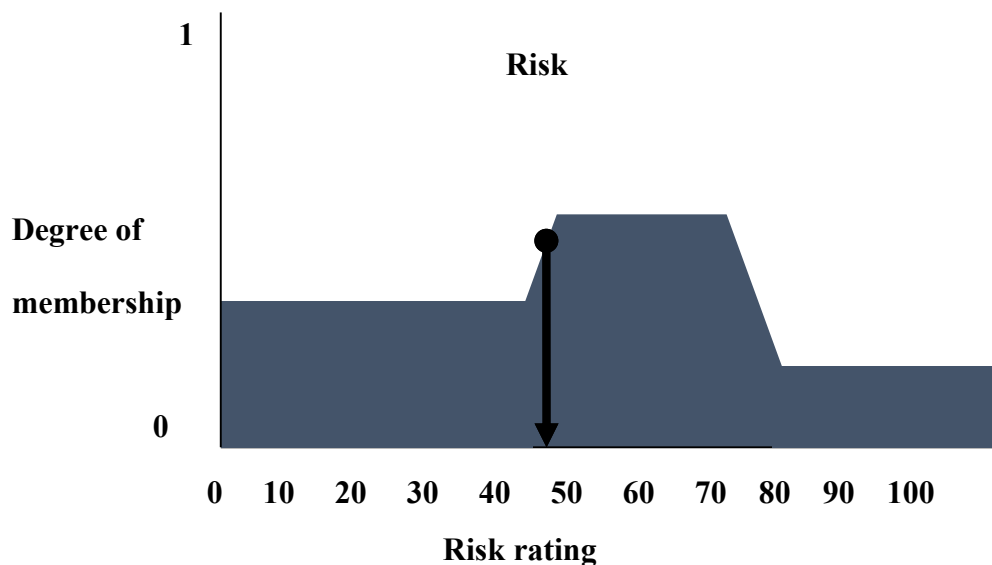


Figure A-6 Defuzzification of risk

## Implementation of fuzzy expert system

The actions of a fuzzy expert system are shaped by the rule base and there are five phases in the construction of this rule base:

1. Identifying and listing the input variables with projected ranges.
2. Identifying and listing the output variables and projected ranges.
3. Defining the fuzzy membership function associated with each input and output variable.
4. Constructing the rule base that will govern the fuzzy controller's operation.
5. Selecting a defuzzification technique to aggregate to arrive at an output.

The above steps are illustrated with a simplified hypothetical example below. The next sections illustrates how to implement the controller of fuzzy expert system that is to be used to rate the vulnerability for water mains. The example uses two inputs: 1) pipe condition 2) buried depth. to arrive at single output (vulnerability rating).

**Step 1: Identifying and listing the input variables with projected ranges.**

There are two input variables: pipe condition and buried depth. There are five ranges each of pipe condition and buried depth (m) as shown inTable A-1 and Table A-2 :

Table A-1 Pipe condition range

Range of linguistic values:	Low	High
Excellent	5	5
Good	4	4
Fair	3	3
Poor	2	2
Failure	1	1

Table A-2 Buried depth range

Range of linguistic values:	Low	High
Large	10	$\infty$
Medium	6	11
Short	4	8
Very short	0	5

### Step 2: Identify and list the linguistic output variables and their numeric ranges

The two inputs will be used to arrive at single output which is the vulnerability rating whose range is shown in Table A-3.

Table A-3 Vulnerability rating range

Range of linguistic values:	Low	High
Full	70	100
Medium	40	85
Slight	0	45

### Step 3: Defining the fuzzy membership function associated with each input and output variable.

The low and high values are utilized to set the boundary of each membership function for the inputs and output. For the pipe condition, the pipe can be only in one position and therefore the membership function is linear as depicted in Figure A-7. On the other hand, the classification of the buried depth into various linguistic ranges is subjective and a triangular, trapezoidal, bell shape ...ect. Can be selected based on the experts elicited opinions. The vulnerability rating shares

the same concept with buried depth as shown in Figure A-8 and Figure A-9. The height of each function is 1.0 and the function bounds do not exceed the high and low ranges listed for each range.

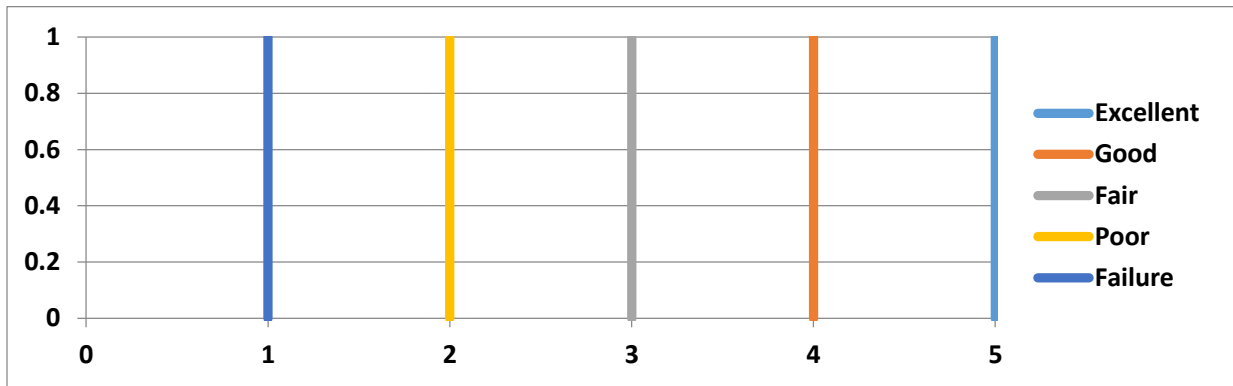


Figure A-7 Pipe condition membership function

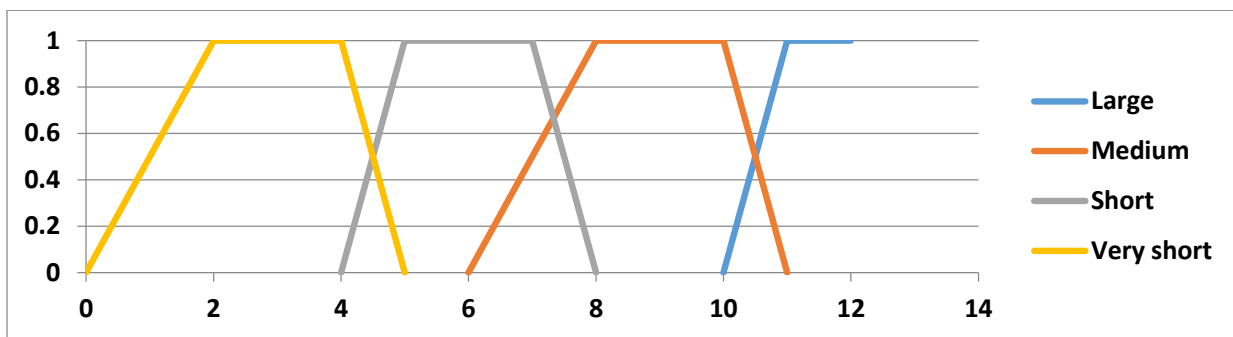


Figure A-8 Buried depth membership function

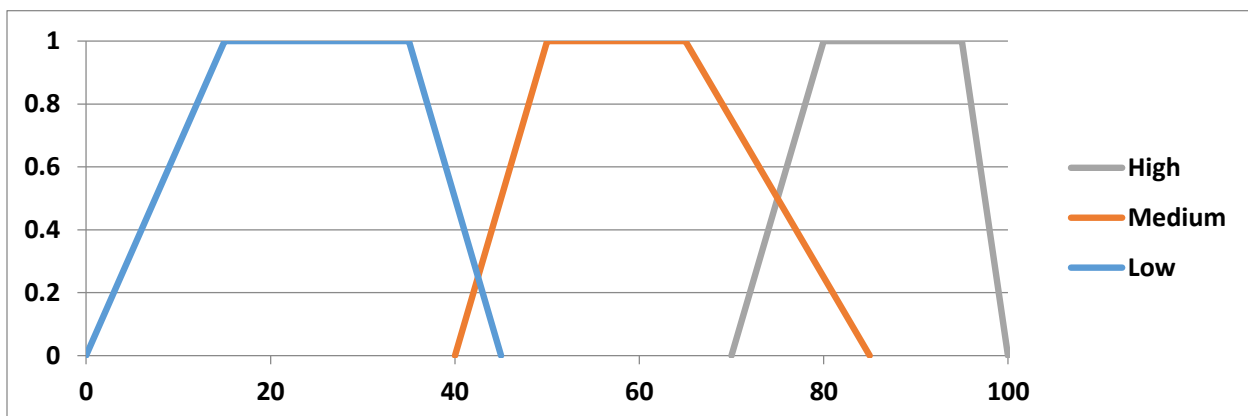


Figure A-9 Vulnerability rating membership function

**Step 4: Constructing the rule base that will govern the fuzzy controller's operation.**

A rule base can be visualized as a matrix of combinations of each of the input range variable and with the intersection of each matrix input, the associated output range variable can be determined. The rule base matrix for this simple example problem has only 25 rules that describe the interaction between input and output variables. Each entry in the rule base is defined by AND which combine the inputs to produce the output. As an example, the shaded matrix entry above means:

IF pipe condition is poor AND IF buried depth is large THEN vulnerability rating is low.

IF pipe condition is failure AND IF buried depth is short THEN vulnerability rating is high.

Table A-4 Rule base matrix

<div>Pipe Condition</div> <div>Buried depth(m)</div>	Excellent	Good	Fair	Poor	Failure
Large	Low	Low	Low	Low	Low
Medium	Low	Low	Medium	Medium	Medium
Short	Medium	Medium	High	High	High
Very short	Medium	Medium	High	High	High

It should be noted that when (n) input variables are considered, an (n) matrix surface is expected.

#### Step 5: Selecting a defuzzification technique to arrive at a single output.

By applying the centroid defuzzification which was described already on the following inputs:

- Pipe condition = 4
- Buried depth = 7 m



The inputs are fuzzified to determine which membership functions are activated and to what degree. Three membership functions are activated: the pipe condition function for condition 4, and the buried depth functions for medium and short. For the pipe condition at 4, the membership function is discrete and therefore the membership function is 1 and can be written as:

$$M_{poor}(4) = 1 \dots\dots\dots \text{Equation A-2}$$

The membership of the buried depth of 7 m in the fuzzy set for short is 0.65 and in the fuzzy set for medium is 0.65. Mathematically, they are denoted as

$$M_{short}(6.5) = 0.65 \dots\dots\dots \text{Equation A-3}$$

$$M_{medium}(6.5) = 0.65 \dots\dots\dots \text{Equation A-4}$$

This results in two rules firing in the rule base matrix as shown in

Table A-4 Rule base matrix

Buried depth(m) \ Pipe Condition	Pipe Condition				
	Excellent	Good	Fair	Poor	Failure
Large	Low	Low	Low	Low	Low
Medium	Low	Low	Medium	Medium	Medium
Short	Medium	Medium	High	High	High
Very short	Medium	Medium	High	High	High

It should be noted that when (n) input variables are considered, an (n) matrix surface is expected.

#### Step 5: Selecting a defuzzification technique to arrive at a single output.

By applying the centroid defuzzification which was described already on the following inputs:

- Pipe condition = 4
- Buried depth = 7 m

. Next, the membership values are combined together using the AND (min) operator for each rule combination:

$$\text{Rule 1: } M_{\text{poor}} \text{ AND } M_{\text{short}} = \min(1.0, 0.65) = 0.65$$

$$\text{Rule 2: } M_{\text{poor}} \text{ AND } M_{\text{medium}} = \min(1.0, 0.65) = 0.65$$

Next the output value for each rule is determined by truncating the corresponding output membership function using its firing strength.

## **Appendix B : MAUT Survey**

Dear Sir/ Madame,

My name is Ahmed A. Youssef, PhD student in the area of Construction Engineering and Management at Concordia University, Montreal, Canada. I am currently conducting a research on vulnerability assessment of interdependent infrastructure networks. The focus of this research is on water, sewer and road assets.

I would like to seek your assistance in my research as I am currently trying to gather information about factors used to assess vulnerability of infrastructure networks to be used in my database. I would be grateful if you could complete the attached questionnaire.

The information gathered from the questionnaire will be used to develop a computer program to assess vulnerability of interdependent networks. Please be assured that all information shared will be strictly confidential and used only for academic purposes. Please do not hesitate to contact me if you need any clarification or additional information. Sharing your valuable information is highly appreciated.

Best regards,

Ahmed A. Youssef

PhD student

Department of Building, Civil, & Environmental Engineering

Concordia University Montreal, Quebec Canada

Osama Moselhi, PhD, Professor

1515 St. Catherine W. H3G 1M8 Dep. Building, Civil, & Environmental Engineering – Concordia University Montreal, Quebec Canada

## Questionnaire Form

All responses will remain **STRICTLY CONFIDENTIAL** and will be used for educational and research purposes only.

### PART 1: COMPANY'S PROFILE

**COMPANY'S NAME:** -----

**TITLE OR POSITION OF RESPONDENT:** -----

**ADDRESS:**

-----  
-----  
-----

**TELEPHONE/ FAX / WEBSITE / E-MAIL:**

-----  
-----

**How many years have you been in business; please specify?**

-----

## PART 2: VULNERABILITY ASSESSMENT

Vulnerability assessment, in this survey, measures an asset's degree of susceptibility for structural and/or functional failures triggered by failure of these functions in neighboring assets. For each asset type, you are asked to assign relative weights for each factor of the ten identified factors. You will be subsequently asked to establish utility functions for vulnerability rating as well.

### 1. Water assets:

#### a. Weight assignment

Assume that a hypothetical segment of water is interdependent with a sewer segment or a road segment. Please, try to complete the following table to show the importance of the following factors' weight. The total percentages should sum to 100.

Factor		Weight
Spatial factors	Asset condition	
	Neighboring asset condition	
	Soil type	
	Pipe length	
	Buried depth	
	Pipe diameter	
Functional factors	Number of affected customers	
	Customers type	
	Response time	
	Betweenness centrality	

#### b. Utility functions

For each of the above identified factors, please type to construct a utility function. You are asked to rate your satisfaction over a range of achievement levels on each factor. First start by identifying the highest and lowest values to be assigned arbitrary values with 0 and 1, respectively. Then, try to identify the other three intermediate values.

Vulnerability	Factor	Utility	Values				
Spatial	Asset condition	Satisfaction	1	2	3	4	5
	Neighboring asset condition	Satisfaction	1	2	3	4	5
	Soil type	Satisfaction	Clay	Sand	Gravel	Stone	Rock
	Pipe length (m)	Satisfaction	100	200	300	400	500
	Buried depth (m)	Satisfaction	1	2	3	4	5
	Pipe diameter(mm)	Satisfaction	100	300	500	700	900
Functional	Number of affected customers(in thousands)	Satisfaction	1000	2000	3000	4000	5000
	Customers type	Satisfaction	Domestic		Commercial		Industrial
	Response time (min)	Satisfaction	10	20	30	40	50
	Betweenness centrality	Satisfaction	0.1	0.3	0.6	0.8	1

## 2. Sewer asset

### a. Weight assignment

Assume that a hypothetical segment of sewer is interdependent with a water segment or a road segment. Please, try to complete the following table to show the importance of the following factors' weight. The total percentages should sum to 100.

Factor		Weight
Spatial factors	Asset condition	
	Neighboring asset condition	
	Soil type	
	Pipe length	
	Buried depth	
	Pipe diameter	
Functional factors	Number of affected customers	
	Customers type	
	Response time	
	Betweenness centrality	

### b. Utility functions

For each of the above identified factors, please type to construct a utility function. You are asked to rate your satisfaction over a range of achievement levels on each factor. First start by identifying the highest and lowest values to be assigned arbitrary values with 0 and 1, respectively. Then, try to identify the other three intermediate values.

Vulnerability	Factor	Utility	Values				
Spatial	Asset condition	Satisfaction	1	2	3	4	5
	Neighboring asset condition	Satisfaction	1	2	3	4	5
	Soil type	Satisfaction	Clay	Sand	Gravel	Stone	Rock
	Pipe length (m)	Satisfaction	100	200	300	400	500
	Buried depth (m)	Satisfaction	1	2	3	4	5
	Pipe diameter(mm)	Satisfaction	100	300	500	700	900
Functional	Number of affected customers(in thousands)	Satisfaction	1000	2000	3000	4000	5000
	Customers type	Satisfaction	Domestic		Commercial		Industrial
	Response time (min)	Satisfaction	10	20	30	40	50
	Betweenness centrality	Satisfaction	0.1	0.3	0.6	0.8	1



### 3. Road asset

#### a. Weight assignment

Assume that a hypothetical segment of road is interdependent with a water segment or a sewer segment. Please, try to complete the following table to show the importance of the following factors' weight. The total percentages should sum to 100.

Factor		Weight
Spatial factors	Asset condition	
	Neighboring asset condition	
	Soil type	
	Pipe length	
	Buried depth	
	Pipe diameter	
Functional factors	Average daily traffic	
	Road type	
	Response time	
	Betweenness centrality	

#### b. Utility functions

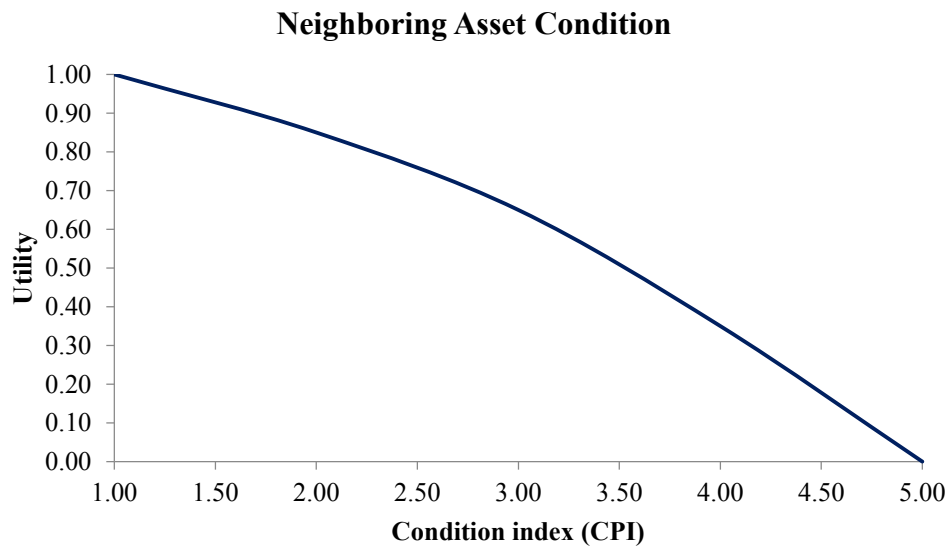
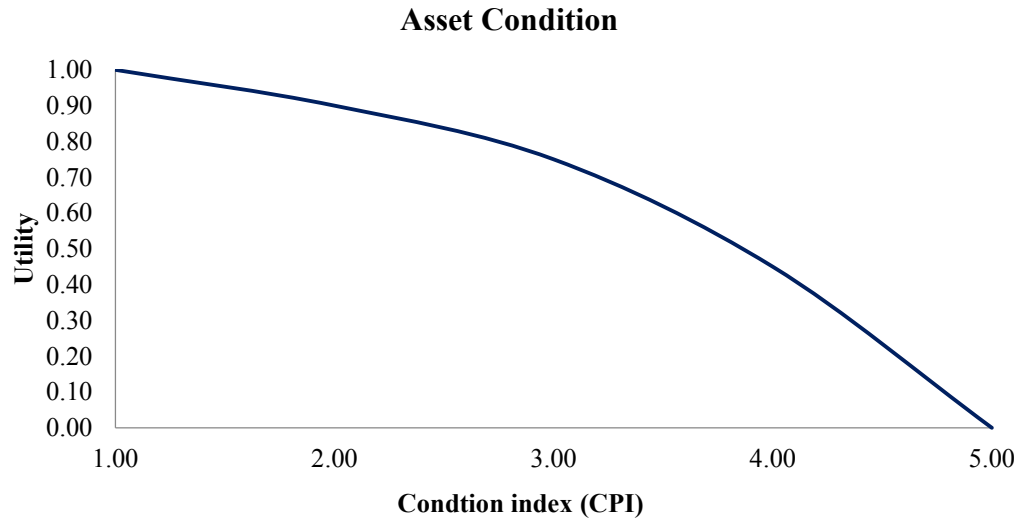
For each of the above identified factors, please type to construct a utility function. You are asked to rate your satisfaction over a range of achievement levels on each factor. First start by identifying the highest and lowest values to be assigned arbitrary values with 0 and 1, respectively. Then, try to identify the other three intermediate values.

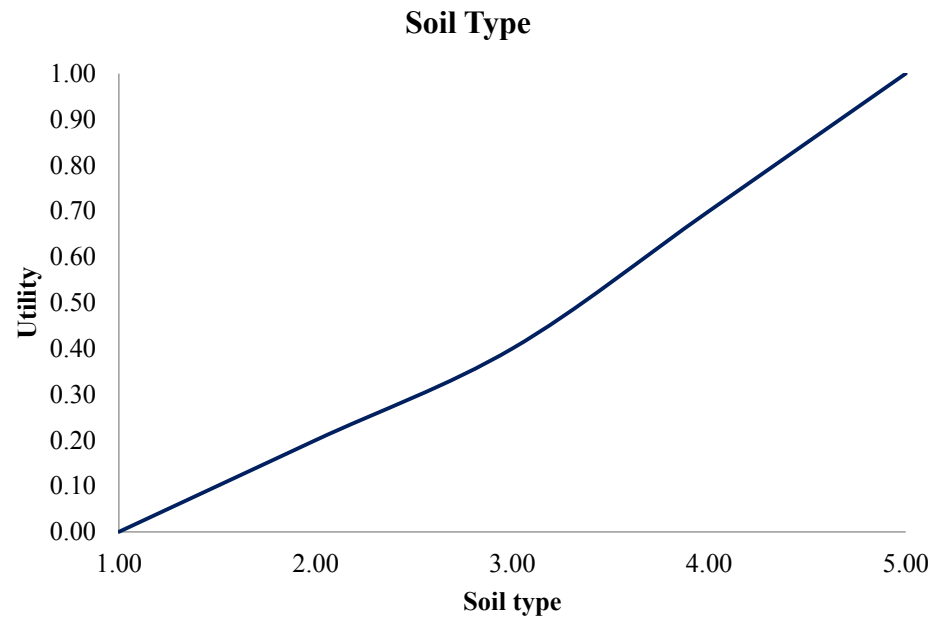
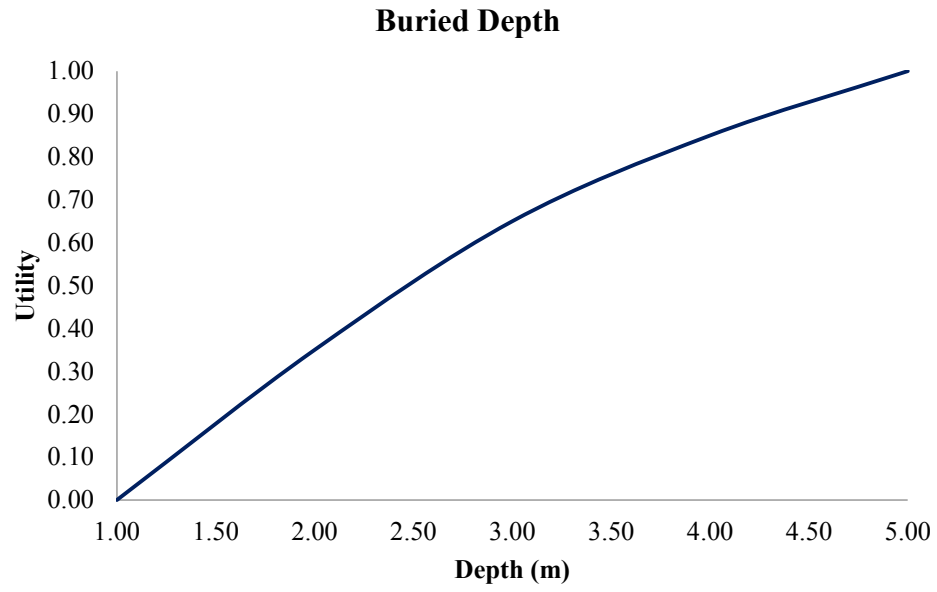
Vulnerability	Factor	Utility	Values				
Spatial	Asset condition	Satisfaction	1	2	3	4	5
	Neighboring asset condition	Satisfaction	1	2	3	4	5
	Soil type	Satisfaction	Clay	Sand	Gravel	Stone	Rock
	Pipe length (m)	Satisfaction	100	200	300	400	500
	Buried depth (m)	Satisfaction	1	2	3	4	5
	Pipe diameter(mm )	Satisfaction	100	300	500	700	900
Functional	Average daily traffic	Satisfaction	Light	Medium		Heavy	
	Road type	Satisfaction	Paved	Gravel	Tar and Gravel	Concrete	
	Response time (min)	Satisfaction	10	20	30	40	50
	Betweenness centrality	Satisfaction	0.1	0.3	0.6	0.8	1

## MAUT results

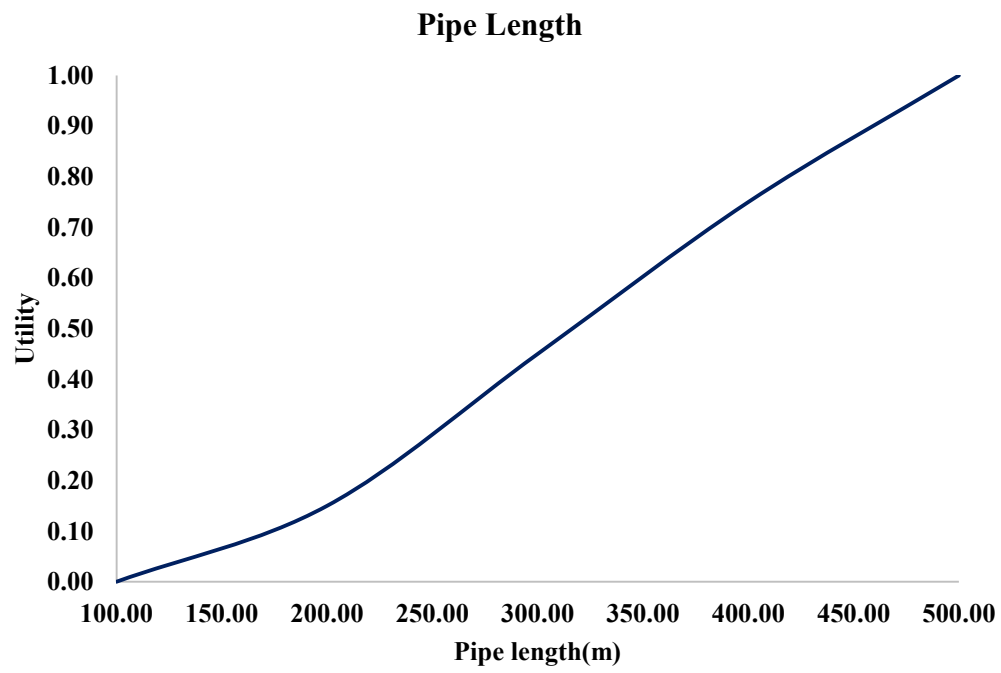
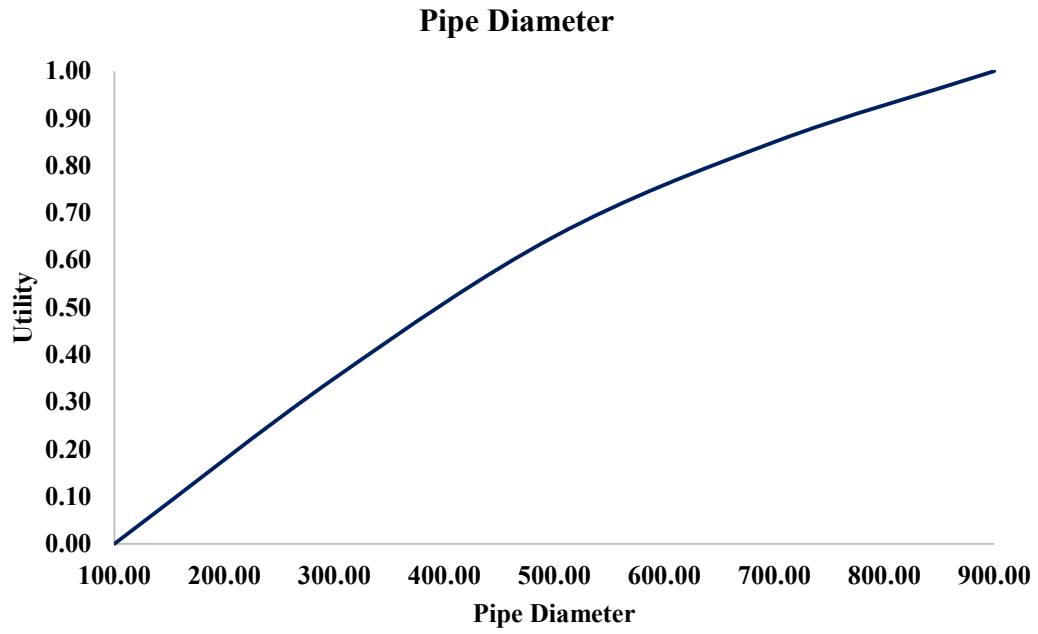
### 1. Water assets:

#### a) Spatial factors

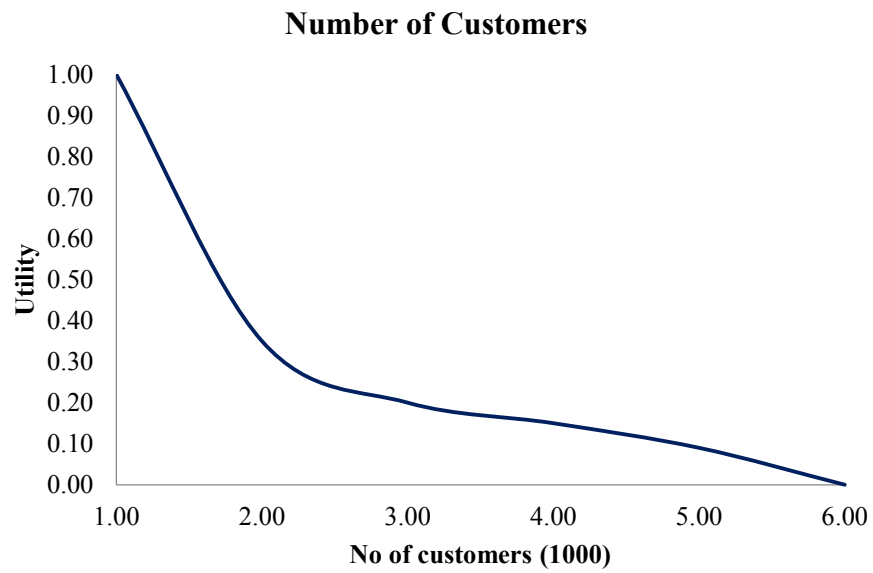
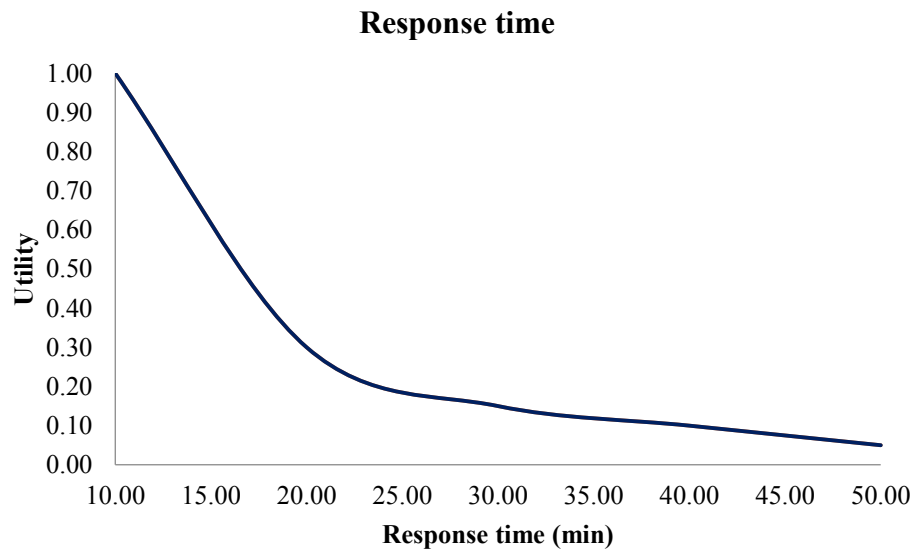


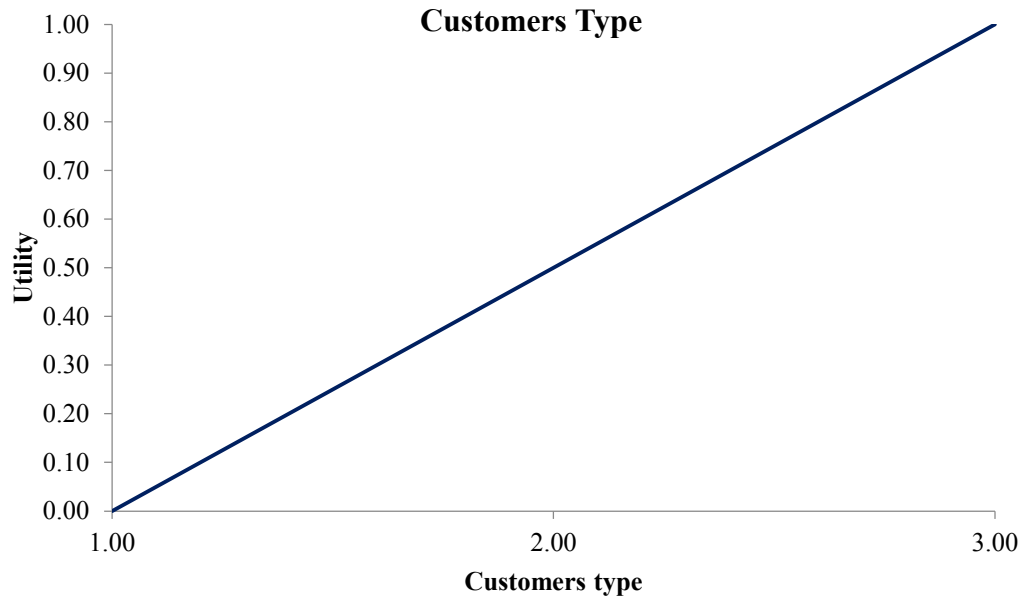


1)Rock. 2)Gavel. 3)Stone. 4) Sand. 5)Clay.

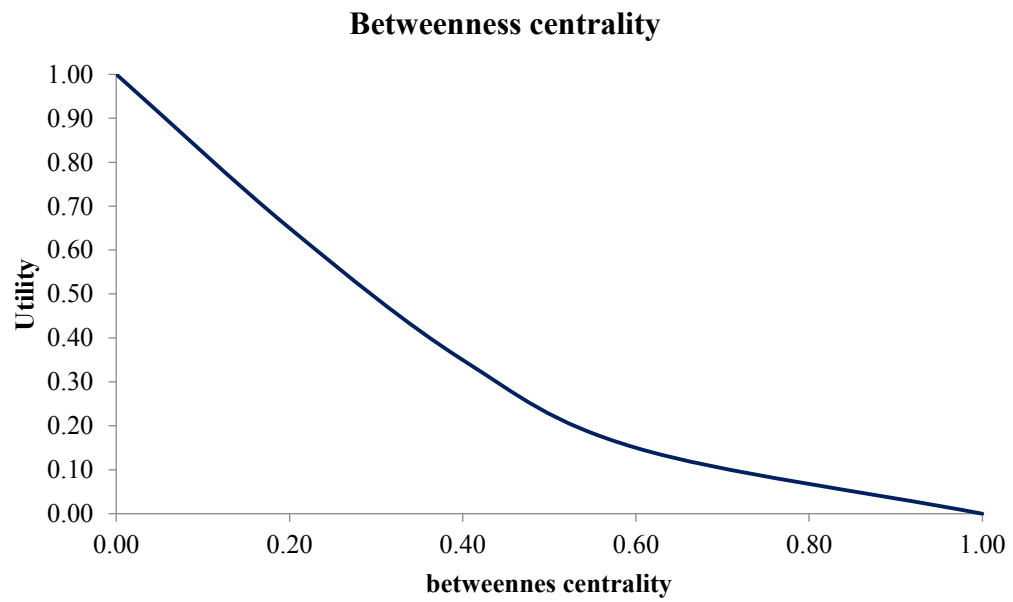


## b) Functional Factors



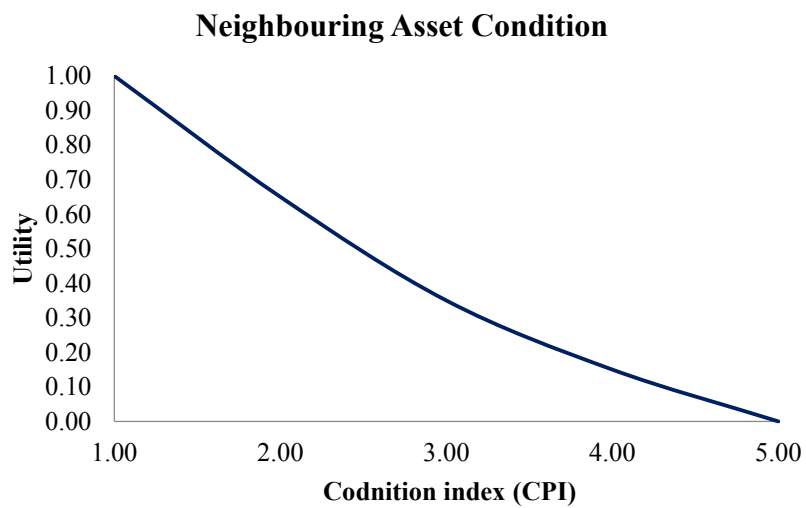
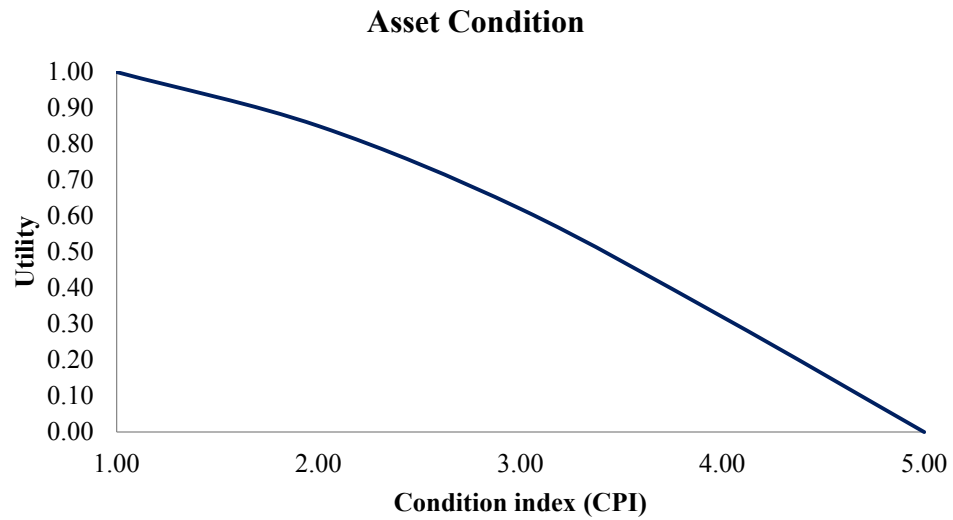


1)Domestic. 2)Commercial. 3)Industrial.

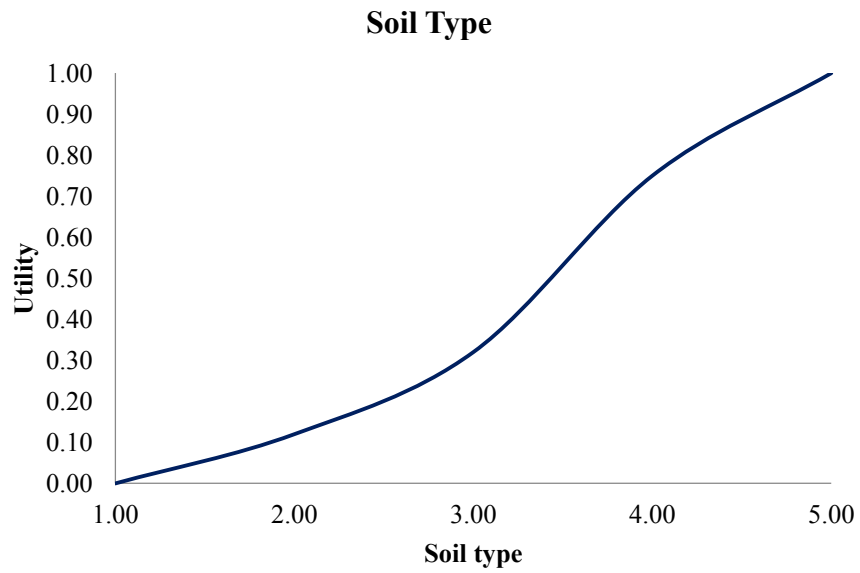
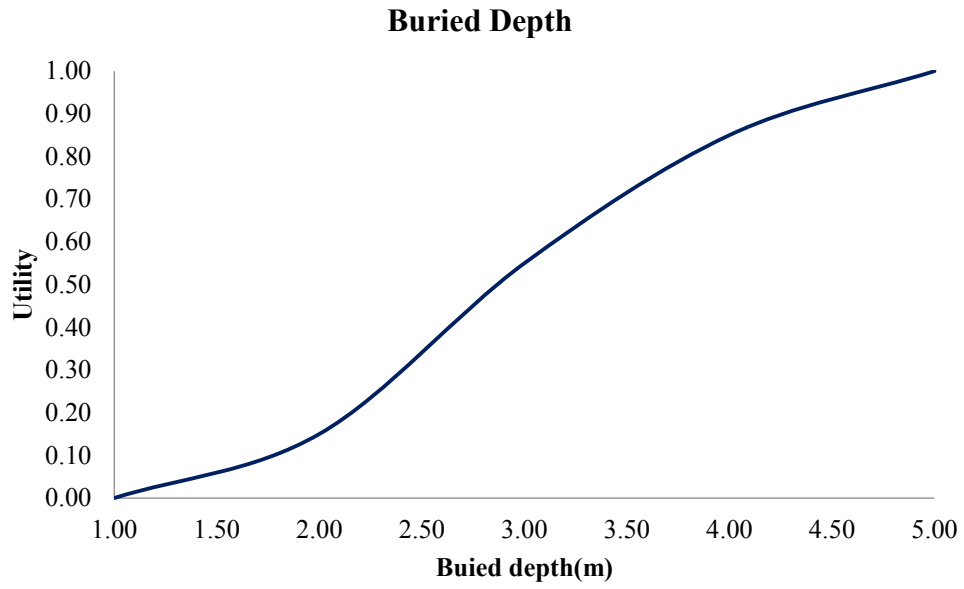


## 2. Sewer assets:

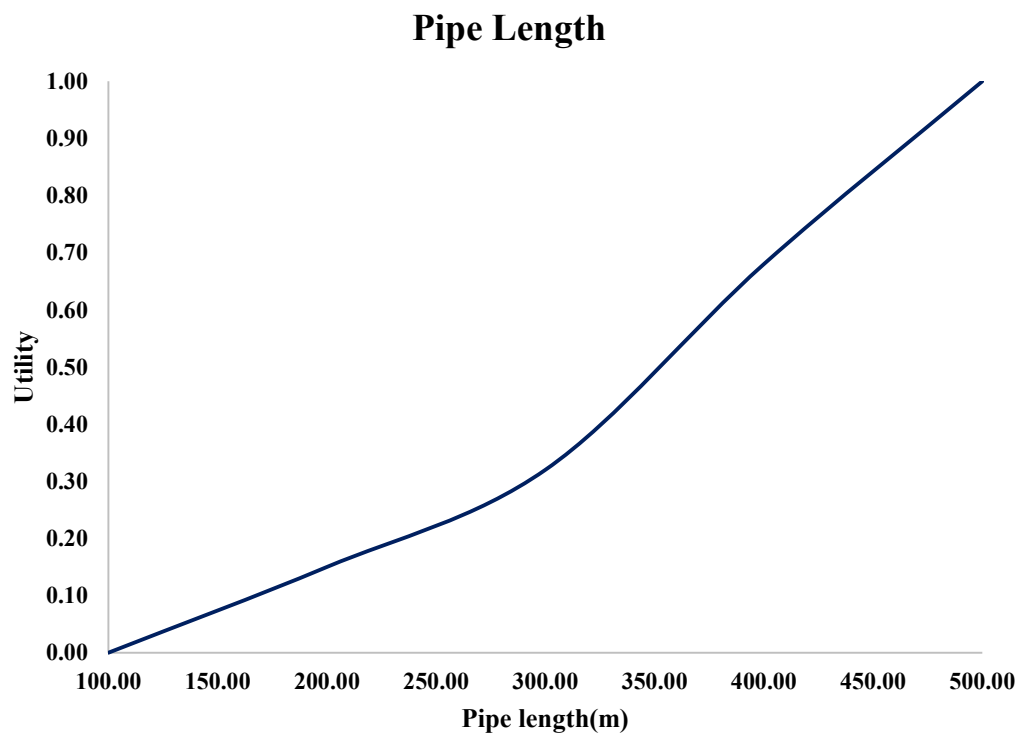
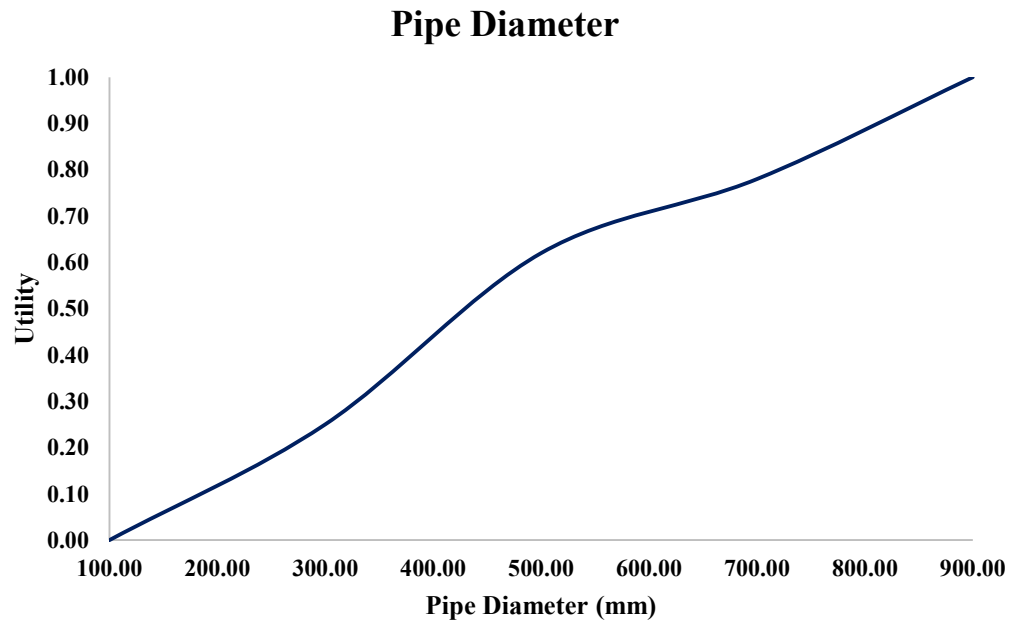
### c) Spatial factors



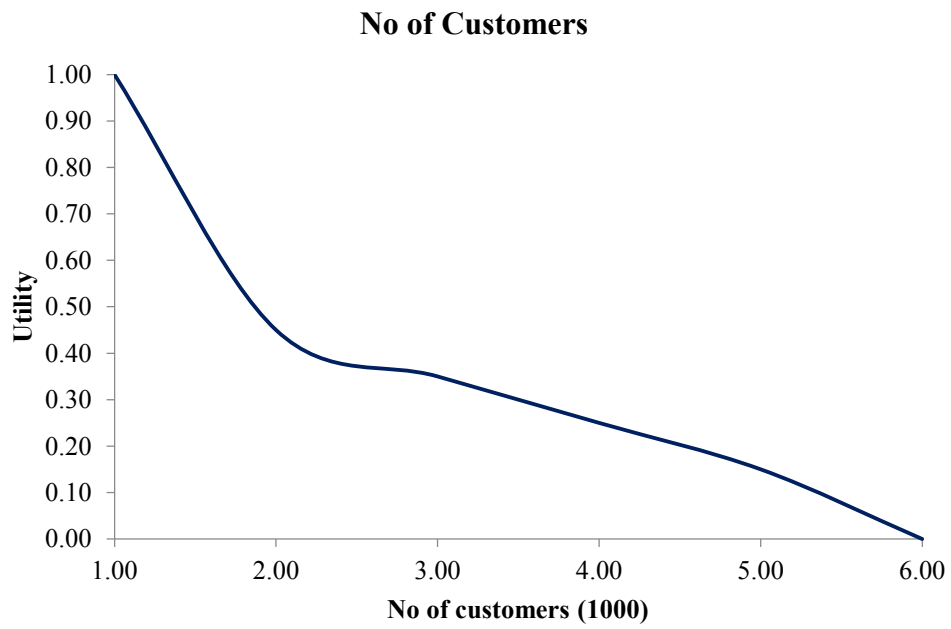
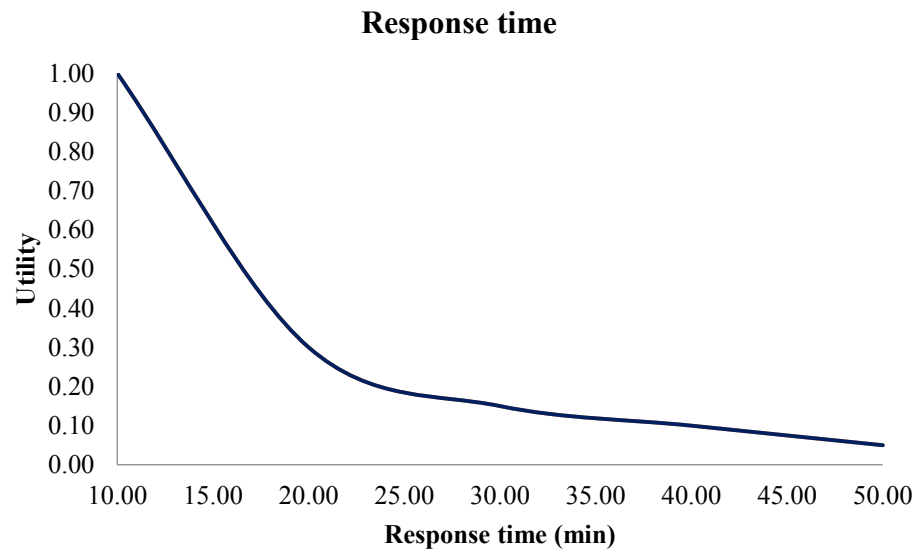


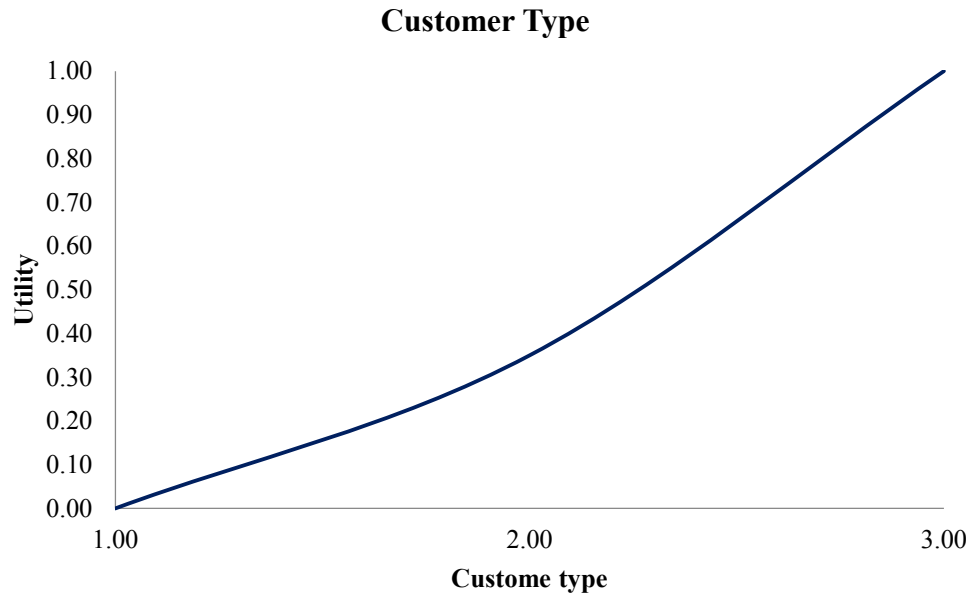


1)Rock. 2)Gavel. 3)Stone. 4)Sand. 5)Clay.

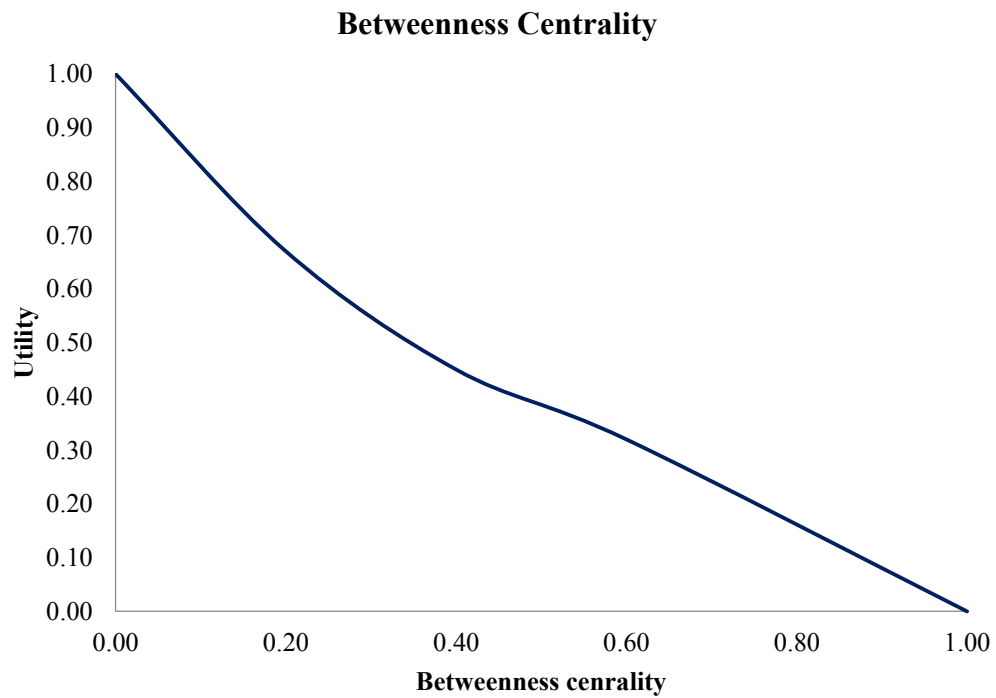


#### d) Functional Factors



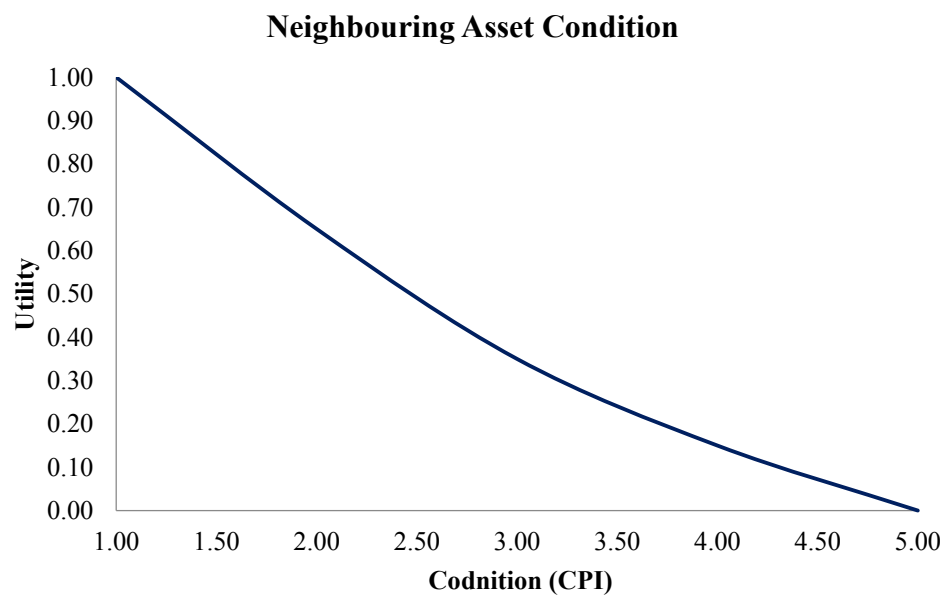
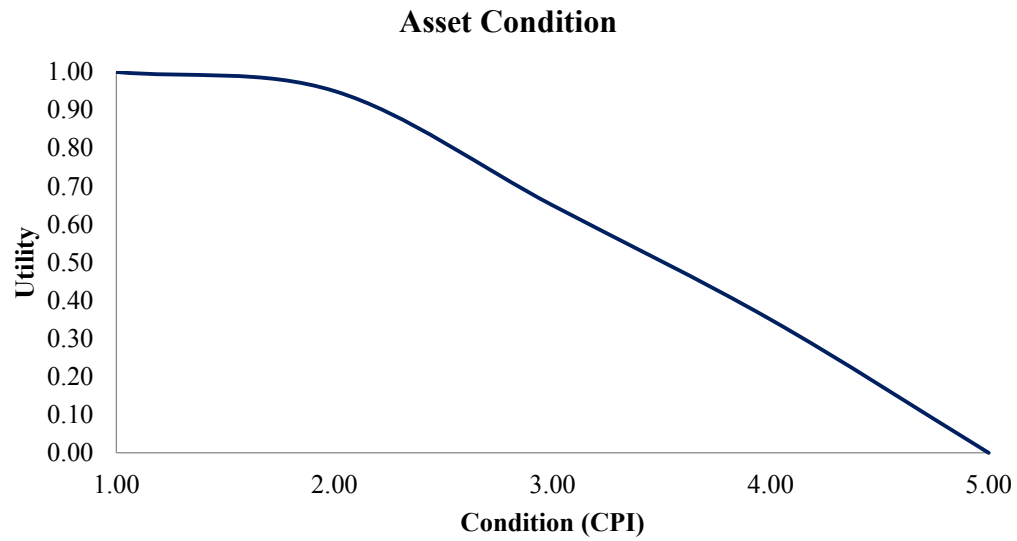


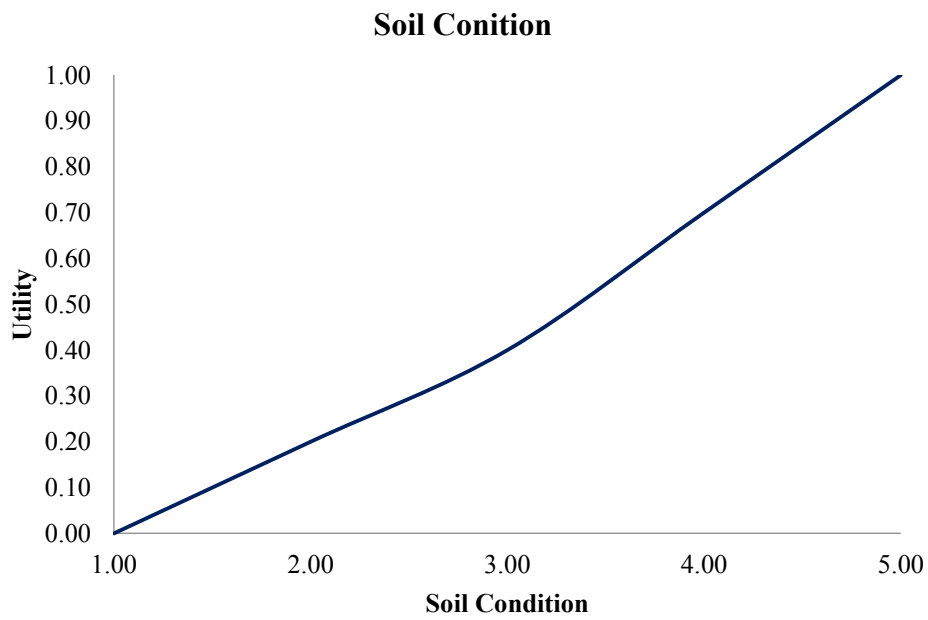
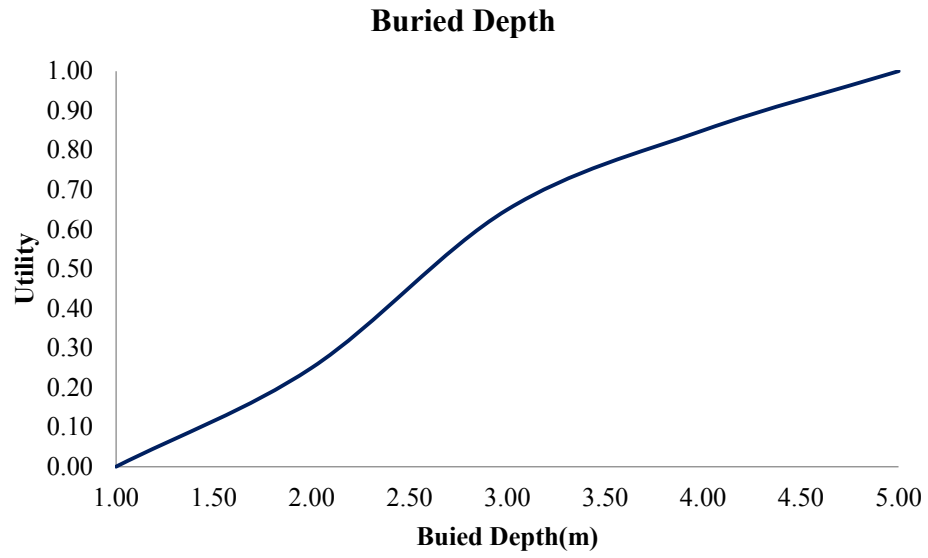
1)Domestic. 2)Commercial. 3)Industrial.



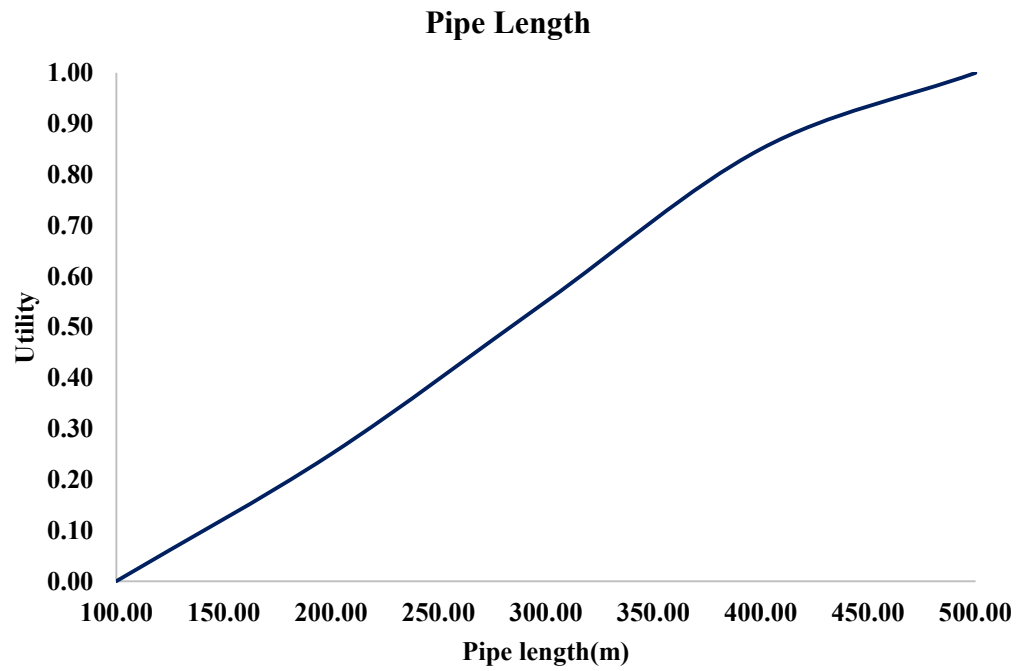
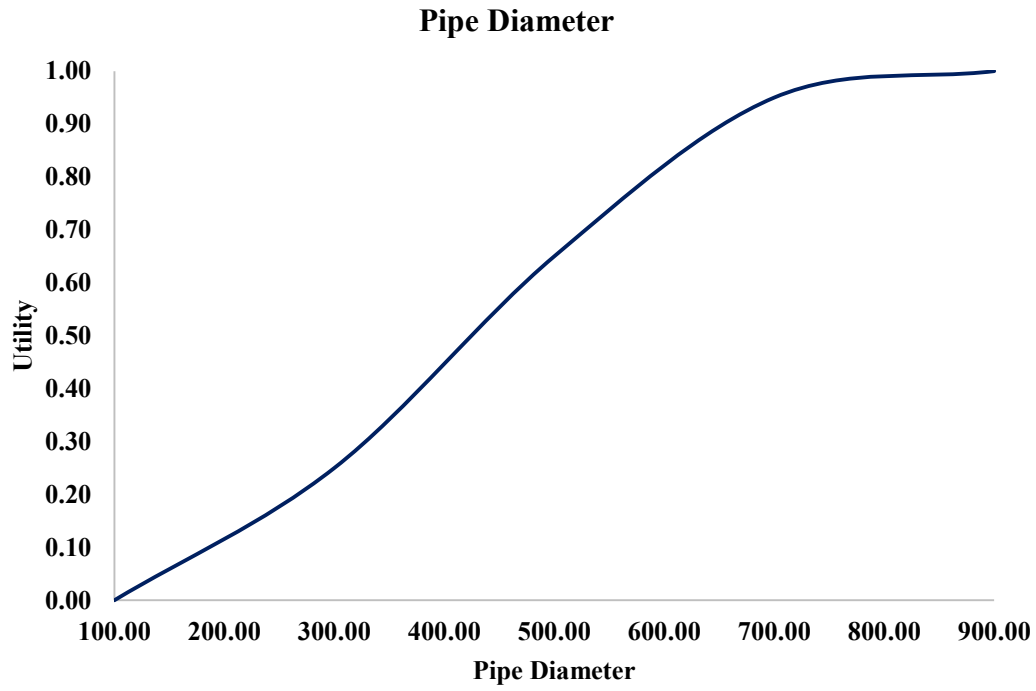
### 3. Road assets:

#### e) Spatial factors

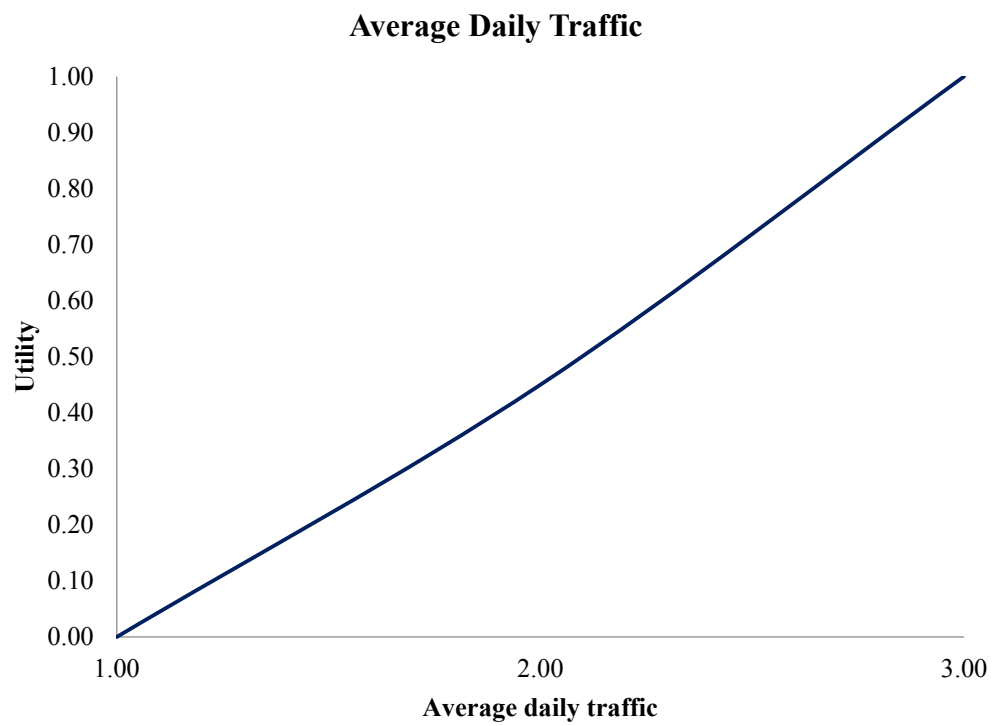
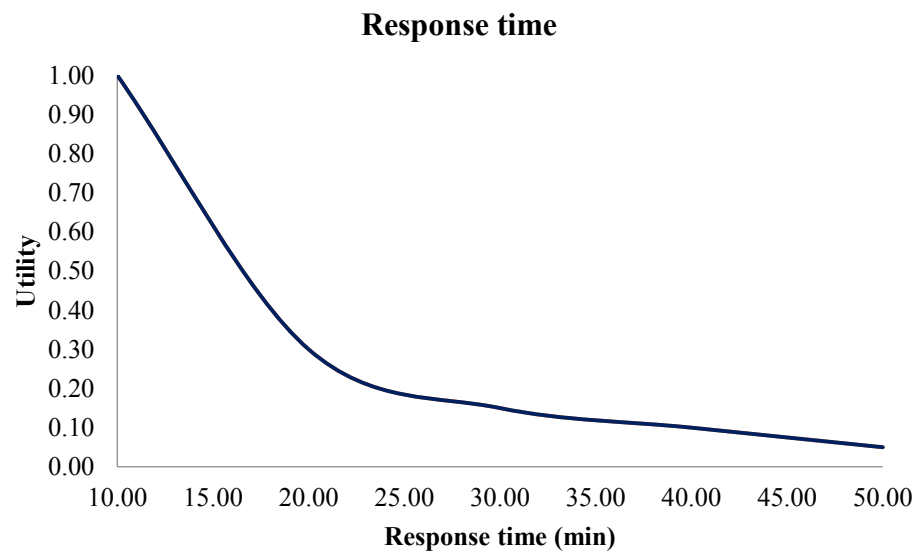




1)Rock. 2)Gavel. 3)Stone. 4) Sand. 5)Clay.

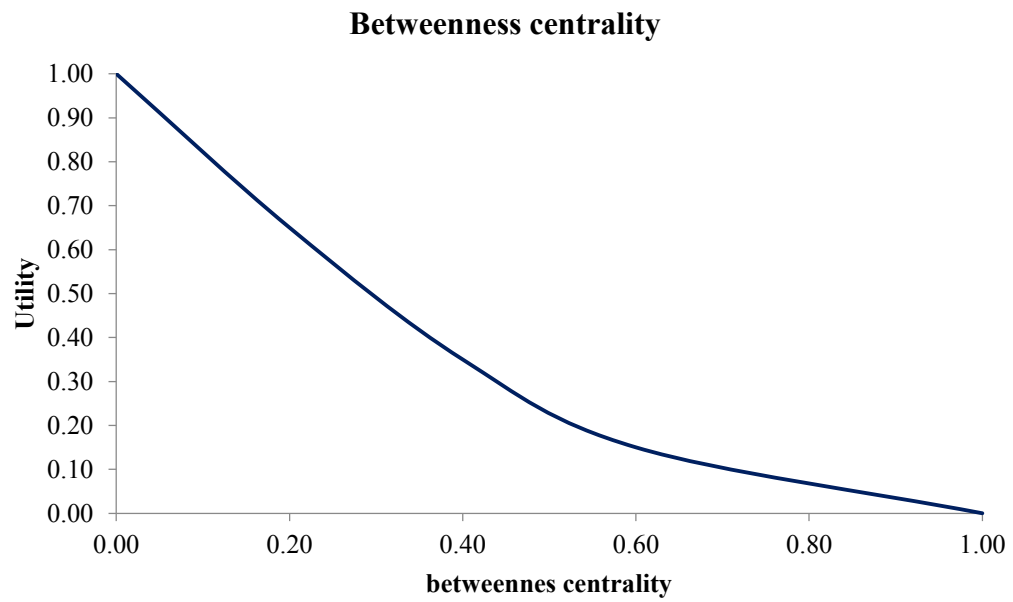
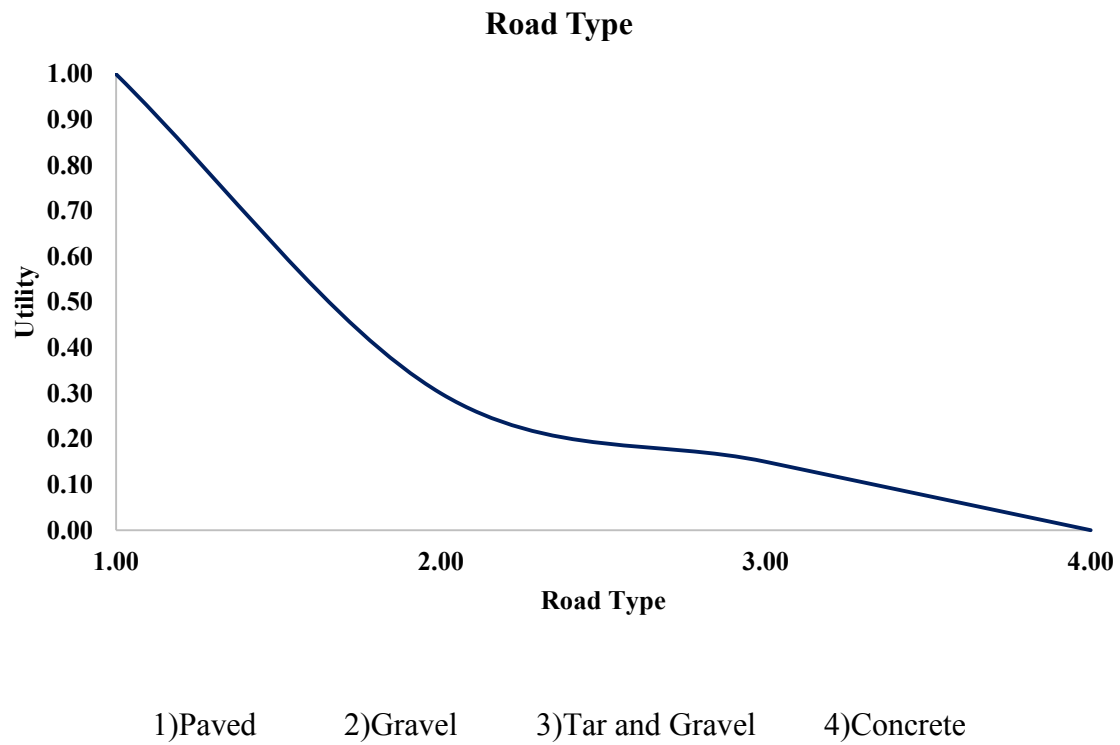


**f) Functional Factors**



1)Light. 2)Medium. 3)Heavy.





## Appendix C : Sample of the SD Output

### (Bundle Level)

#### Policy ID(1) (Sample)

	Water					Road				
Year	Action	Condition	V	Ts	Cost	Action	Condition	Vul	Ts	Cost
1	Do nothing	3	4	60	0	Do nothing	1	6	75	0
2	Do nothing	3.1	4	58	0	Do nothing	1.21	6	72.1	0
3	Do nothing	3.2	4	56.1	0	Do nothing	1.32	6.3	67.2	0
4	Do nothing	3.35	4	52.4	0	Do nothing	1.45	6.4	63.1	0
5	Do nothing	3.47	4	50.2	0	Do nothing	1.57	6.51	57.7	0
6	Do nothing	3.6	4	48.2	0	Do nothing	1.68	6.7	52.4	0
7	Do nothing	3.81	4	45.5	0	Do nothing	1.84	6.9	48.1	0
8	Do nothing	3.97	4	40.5	0	Do nothing	1.92	7.1	44.8	0
9	Major Action	1	1	100	56700	Do nothing	2.01	1	82.1	0
10	Do nothing	1.15	1	99	0	Do nothing	2.2	1	81.8	0

V: Vulnerability rating

Ts: Total Satisfaction

**Policy ID (6) (Sample)**

	Water					Road				
Year	Action	Condition	V	Ts	Cost	Action	Condition	V	Ts	Cost
1	Do nothing	3	4	60	0	Do nothing	1	6	75	0
2	Major Action	1	1.2	100	47561	Do nothing	1.21	6	72.1	0
3	Do nothing	3.2	4	98.3	0	Do nothing	1.32	6.3	67.2	0
4	Do nothing	3.35	4	96.4	0	Do nothing	1.45	6.4	63.1	0
5	Do nothing	3.47	4	94.2	0	Do nothing	1.57	6.51	57.7	0
6	Do nothing	3.6	4	92.2	0	Do nothing	1.68	6.7	52.4	0
7	Do nothing	3.81	4	89.5	0	Do nothing	1.84	6.9	48.1	0
8	Do nothing	3.97	4	87.5	0	Do nothing	1.92	7.1	44.8	0
9	Do nothing	1	1	86.1	0	Do nothing	2.01	1	82.1	0
10	Do nothing	1.15	1	85.3	0	Do nothing	2.2	1	81.8	0

V: Vulnerability rating

Ts: Total Satisfaction

## Appendix D : Coding Samples

/\*

These are code samples for the following functions:

- 1- Importing inputs and exporting outputs.
- 2- Causal loops (R1, R2, R3 and R4).
- 3- Dynamic programming algorithm (selecting intervention actions and sorting best solutions).
- 4- Genetic algorithm (population initialization and sorting).

\*/

// defining the libraries needed for exporting, importing and processing data from excel sheets

using System;

using System.Collections.Generic;

using System.ComponentModel;

using System.Data;

using System.Drawing;

using System.Linq;

using System.Text;

using System.Windows.Forms;

using Excel = Microsoft.Office.Interop.Excel;

namespace Assets\_Inter\_Dependency

{

public partial class Form1 : Form //taking users inputs from user form 1

{

double L1 = 0.0;

double L2 = 0.0;

```

double L = 0.0;
public Form1()
{
    InitializeComponent();
}
private void bt_start_Click(object sender, EventArgs e)
{
    // set mouse cursor to busy while executing
    Cursor.Current = Cursors.WaitCursor;
    // read assets data from execl file
    readXlData();
    Global_Var.bundles_arr = new double[Global_Var.bundles_data.GetLength(0), 25];
    double[] asset_data = new double[10];
    int x = 0; x <= Global_Var.bundles_data.GetLength(0)-1; x++
    // R1
    // calculate vulnerability
    for (int x = 0; x <= Global_Var.bundles_data.GetLength(0)-1; x++)
    {
        label5.Text = (x+1).ToString();
        label5.Refresh();
        label7.Text = Global_Var.bundles_data.GetLength(0).ToString();
        double[] intial_condition = new double[9];
        for (int y = 0; y <= 8; y++)
        {
            Global_Var.bundles_arr[x, y] = Global_Var.bundles_data[x, y];
            asset_data[y] = Global_Var.bundles_data[x, y];
        }
        // set level of service
        Global_Var.bundles_arr[x, 9] = Global_Var.bundles_arr[x, 8];
        // Neighboring Asset Condition
    }
}

```

```

asset_data[9] = Global_Var.bundles_data[x, 17];
// calculate vulnerability
Global_Var.bundles_arr[x, 10] = calculate_Vulnerablity(asset_data);
// calculate total satisfaction for the road
Global_Var.bundles_arr[x, 11] = calculate_road_score(Global_Var.bundles_arr[x, 8],
Global_Var.bundles_arr[x, 9], Global_Var.bundles_arr[x, 10]);
// set constrains conditions
intial_condition[0] = Global_Var.bundles_arr[x, 8];
intial_condition[1] = Global_Var.bundles_arr[x, 9];
intial_condition[2] = Global_Var.bundles_arr[x, 10];
intial_condition[3] = Global_Var.bundles_arr[x, 11];
for (int y = 0; y <= 8; y++)
{
    Global_Var.bundles_arr[x, y + 12] = Global_Var.bundles_data[x, y + 9];
    asset_data[y] = Global_Var.bundles_data[x, y + 9];
}
// R3
// set level of service
Global_Var.bundles_arr[x, 21] = Global_Var.bundles_arr[x, 20];
// Neighboring Asset Condition
asset_data[9] = Global_Var.bundles_arr[x, 8];
// calculate vulnerability
Global_Var.bundles_arr[x, 22] = calculate_Vulnerablity(asset_data);
// calculate score
Global_Var.bundles_arr[x, 23] = calculate_water_score(Global_Var.bundles_arr[x, 20],
Global_Var.bundles_arr[x, 21], Global_Var.bundles_arr[x, 22]);
// calculate total score
Global_Var.bundles_arr[x, 24] = Global_Var.bundles_arr[x, 11] +
Global_Var.bundles_arr[x, 23];
// set constrains
intial_condition[4] = Global_Var.bundles_arr[x, 20];

```

```

intial_condition[5] = Global_Var.bundles_arr[x, 21];
intial_condition[6] = Global_Var.bundles_arr[x, 22];
intial_condition[7] = Global_Var.bundles_arr[x, 23];
intial_condition[8] = Global_Var.bundles_arr[x, 24];
// optimize intervention actions at bundle level (using Dynamic programming)
find_policy(x);
// rank the senarios
for (int i = 0; i <= 99; i++)
{
    for (int y = 0; y <= 8; y++)
    {
        asset_data[y] = Global_Var.bundles_data[x, y];
    }

    asset_data[8] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_log
    ger[i, Global_Var.intervention_period]), 8], 0);

    asset_data[9] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_log
    ger[i, Global_Var.intervention_period]), 18], 0);

    // set level of service

    double los1 = asset_data[8];

    // calculate road vulnerability

    double vul1 = calculate_Vulnerablity(asset_data);

    // calculate vulnerability score

    double road_score = calculate_road_score(asset_data[8], los1, vul1);

    for (int y = 0; y <= 8; y++)
    {
        asset_data[y] = Global_Var.bundles_data[x, y + 9];
    }

    asset_data[8] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_logge
    r[i, Global_Var.intervention_period]), 18], 0);

```

```

asset_data[9] =
Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_logge
r[i, Global_Var.intervention_period]), 8], 0);

// set level of service

double los2 = asset_data[8];

// calculate water vulnerability

double vul2 = calculate_Vulnerablity(asset_data);

// calculate score

double water_score = calculate_road_score(asset_data[8], los2, vul2);

//R4

// calculate total score for the bundle

double total_score = road_score + water_score;

Global_Var.Senario_ranking_arr[i, 0] = i;

Global_Var.Senario_ranking_arr[i, 1] = total_score;
}

// ranking array bubble sort (for best scenarios)
for (int i = 99; i >= 1; i--)
{
    for (int j = 0; j <= i - 1; j++)
    {
        if (Global_Var.Senario_ranking_arr[j, 1] > Global_Var.Senario_ranking_arr[j + 1, 1])
        {
            //swap the two values

            double temp0 = Global_Var.Senario_ranking_arr[j, 0];
            double temp1 = Global_Var.Senario_ranking_arr[j, 1];
            Global_Var.Senario_ranking_arr[j, 0] = Global_Var.Senario_ranking_arr[j + 1, 0];
            Global_Var.Senario_ranking_arr[j, 1] = Global_Var.Senario_ranking_arr[j + 1, 1];
            Global_Var.Senario_ranking_arr[j + 1, 0] = temp0;
            Global_Var.Senario_ranking_arr[j + 1, 1] = temp1;
        }
    }
}

```



```

    }
}
// rank the rest of scenarios
for (int i = 100; i <= Global_Var.Senario_counter.GetLength(0) - 1; i++)
{
    // flag to see if new score need to be recorded
    int rank_flag = -1;
    for (int y = 0; y <= 8; y++)
    {
        asset_data[y] = Global_Var.bundles_data[x, y];
    }
    asset_data[8] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_logge
r[i, Global_Var.intervention_period]), 8], 0);
    asset_data[9] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_logge
r[i, Global_Var.intervention_period]), 18], 0);
    // set level of service
    double los1 = asset_data[8];
    // calculate road vulnerability
    double vul1 = calculate_Vulnerablity(asset_data);
    // calculate score
    double road_score = calculate_road_score(asset_data[8], los1, vul1);
    for (int y = 0; y <= 8; y++)
    {
        asset_data[y] = Global_Var.bundles_data[x, y + 9];
    }
    asset_data[8] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_log
ger[i, Global_Var.intervention_period]), 18], 0);
    asset_data[9] =
    Math.Round(Global_Var.action_logger[Convert.ToInt32(Global_Var.Senario_log
ger[i, Global_Var.intervention_period]), 8], 0);

```

```

// set level of service
double los2 = asset_data[8];
// calculate water vulnerability
double vul2 = calculate_Vulnerablity(asset_data);
// calculate score
double water_score = calculate_road_score(asset_data[8], los2, vul2);
// calculate total score
double total_score = road_score + water_score;
for (int h = 0; h <= 9; h++)
{
    if (total_score > Global_Var.Senario_ranking_arr[h, 1])
    {
        rank_flag++;
    }
}
if (rank_flag > -1)
{
    for (int nrow = 0; nrow <= rank_flag - 1; nrow++)
    {
        for (int ncol = 0; ncol <= 1; ncol++)
        {
            Global_Var.Senario_ranking_arr[nrow, ncol] =
            Global_Var.Senario_ranking_arr[nrow + 1, ncol];
        }
    }
    Global_Var.Senario_ranking_arr[rank_flag, 0] = i;
    Global_Var.Senario_ranking_arr[rank_flag, 1] = total_score;
}
}

// extracting the solutions at bundle level

```

```

Excel.Application xlApp = new Excel.Application();
xlApp.Visible = false;
//Excel.Workbook wb;
//Excel.Worksheet ws;

Excel.Workbook wb =
xlApp.Workbooks.Add(Excel.XlWBATemplate.xlWBATWorksheet);

Excel.Worksheet ws = (Excel.Worksheet)wb.Worksheets.get_Item(1);

Excel.Range rng = ws.Cells.get_Resize(Global_Var.Senario_ranking_arr.GetLength(0),
Global_Var.Senario_ranking_arr.GetLength(1));

rng.Value2 = Global_Var.Senario_ranking_arr;
    for (int i = 99; i >= 80; i--)
    {
        //wb = xlApp.Workbooks.Add(Excel.XlWBATemplate.xlWBATWorksheet);
        ws = (Excel.Worksheet)wb.Worksheets.Add();

xlApp.Cells[1, 1] = "Senario #" + Convert.ToString(Global_Var.Senario_ranking_arr[i, 0]);
        xlApp.Cells[2, 1] = "Year";
        xlApp.Cells[2, 2] = "Road Action";
        xlApp.Cells[2, 3] = "Road Condition";
        xlApp.Cells[2, 4] = "Road LOS";
        xlApp.Cells[2, 5] = "Road Vul";
        xlApp.Cells[2, 6] = "Road Action Cost";
        xlApp.Cells[2, 7] = "Road Score";
        xlApp.Cells[2, 8] = "Water Action";
        xlApp.Cells[2, 9] = "Water Condition";
        xlApp.Cells[2, 10] = "Water LOS";
        xlApp.Cells[2, 11] = "Water Vul";
        xlApp.Cells[2, 12] = "Water Action Cost";
        xlApp.Cells[2, 13] = "Water Score";
        xlApp.Cells[2, 14] = "Total Cost";
        xlApp.Cells[2, 15] = "Total Score";
    }

```

```

xlApp.Cells[3, 1] = 0;
xlApp.Cells[3, 2] = "intial";
xlApp.Cells[3, 3] = intial_condition[0];
xlApp.Cells[3, 4] = intial_condition[1];
xlApp.Cells[3, 5] = intial_condition[2];
xlApp.Cells[3, 6] = 0;
xlApp.Cells[3, 7] = intial_condition[3];
xlApp.Cells[3, 8] = "intial";
xlApp.Cells[3, 9] = intial_condition[4];
xlApp.Cells[3, 10] = intial_condition[5];
xlApp.Cells[3, 11] = intial_condition[6];
xlApp.Cells[3, 12] = 0;
xlApp.Cells[3, 13] = intial_condition[7];
xlApp.Cells[3, 14] = 0;
xlApp.Cells[3, 15] = intial_condition[8];
int senario_index = Convert.ToInt32(Global_Var.Senario_ranking_arr[i, 0]);
for (int n = 1; n <= Global_Var.intervention_period; n++)
{
    xlApp.Cells[n + 3, 1] = n;
    if
    (Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 1], 0) == 1)
    {
        xlApp.Cells[n + 3, 2] = "Do Nothing";
    }
    if
    (Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 1], 0) == 2)
    {
        xlApp.Cells[n + 3, 2] = "Minor";
    }
}

```

```

if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_ind
ex, n], 1], 0) == 3)
{
    xlApp.Cells[n + 3, 2] = "Major";
}
if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_ind
ex, n], 1], 0) == 4)
{
    xlApp.Cells[n + 3, 2] = "Replace";
}
xlApp.Cells[n + 3, 3] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 8], 0);
xlApp.Cells[n + 3, 4] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 8], 0);
for (int y = 0; y <= 8; y++)
{
    asset_data[y] = Global_Var.bundles_data[x, y];
}
asset_data[8] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 8], 0);
asset_data[9] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 18], 0);
// Genetic algorithm
// set level of service
double los1 = asset_data[8];
// calculate road vulnerability
double vul1 = calculate_Vulnerablity(asset_data);
// calculate score

```

```

double road_score = calculate_road_score(asset_data[8], los1, vul1);
xlApp.Cells[n + 3, 5] = vul1;
xlApp.Cells[n + 3, 6] =
Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 19];
xlApp.Cells[n + 3, 7] = road_score;
if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 12], 0) == 1)
{
    xlApp.Cells[n + 3, 8] = "Do Nothing";
}
if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 12], 0) == 2)
{
    xlApp.Cells[n + 3, 8] = "Minor";
}
if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 12], 0) == 3)
{
    xlApp.Cells[n + 3, 8] = "Major";
}
if
(Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 12], 0) == 4)
{
    xlApp.Cells[n + 3, 8] = "Replace";
}
xlApp.Cells[n + 3, 9] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 18], 0);

```

```

xlApp.Cells[n + 3, 10] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 18], 0);

for (int y = 0; y <= 8; y++)
{
    asset_data[y] = Global_Var.bundles_data[x, y + 9];
}

asset_data[8] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 18], 0);

asset_data[9] =
Math.Round(Global_Var.action_logger[Global_Var.Senario_logger[senario_inde
x, n], 8], 0);

// set level of service

double los2 = asset_data[8];

// calculate water vulnerablity

double vul2 = calculate_Vulnerablity(asset_data);

// calculate score

double water_score = calculate_road_score(asset_data[8], los2, vul2);

// calculate total score

double total_score = road_score + water_score;

xlApp.Cells[n + 3, 11] = vul2;

xlApp.Cells[n + 3, 12] =
Global_Var.action_logger[Global_Var.Senario_logger[senario_index, n], 21];

xlApp.Cells[n + 3, 13] = water_score;

xlApp.Cells[n+3,14]=Global_Var.action_logger[Global_Var.Senario_logger[sena
rio_index, n], 19]+ Global_Var.action_logger[Global_Var.Senario_logger[senario_index,
n], 21];

```